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People analytics—A scoping review of conceptual boundaries and value propositions

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ABSTRACT

This mixed-method 'scoping review' mapped the emergence of the term People Analytics (PA), the value propositions offered by vendors of PA tools and services and the PA skillsets being sought by professionals. Analysis of academic research and online search traffic since 2002 revealed changes in the relative trajectory of PA and conceptually related terms over the past fifteen years, indicating both the re-branding of similar innovations and a differentiation of priorities and communities of practice. The market in commercial PA tools and services is diverse, offering numerous functional and strategic benefits, although published evidence of these outcomes remains sparse. Companies marketing PA systems and services emphasise benefits to employers more than to personnel. Across the sources examined, including specialised online courses, PA was largely aligned with HRM, however its development reflects the shifting focus of HR departments from supporting functional to strategic organisational requirements. Consideration of ethical issues was largely absent.

1. Introduction

In an increasingly digitised society, interest in the use of so called big (and small) data has never been greater. Data analytic techniques, of varying sophistication, are being used to understand social phenomena, evaluate policies, tailor consumer marketing, predict voting behaviour, enable precision medicine and a host of other real-world applications (Raguseo, 2018). Understanding and optimising the workforce is a key part of this trend (Edwards & Edwards, 2016; Sullivan, 2013). In many ways, this echoes nineteenth century notions of organisations as machines, to be fine-tuned to maximise outputs and minimise waste, with employees seen as components to be stratified, incentivised, deployed and shed for maximum effectiveness. Although most organisational theorists and leaders now recognise organisations as complex adaptive socio-technical systems (Schneider & Somers, 2006) interest in using data analytics and visualisation tools to render this complexity into a more comprehensible and actionable forms is growing (Gandomi & Haider, 2015).

Within this context, the term 'People Analytics' (PA) has been appearing with greater frequency in executive leadership and Human Resources Management (HRM) circles (Deloitte, 2017). PA promises to help organisations understand their workforce as a whole, as departments or work groups, and as individuals, by making data about employee attributes, behaviour and performance more accessible, interpretable and actionable (Pape, 2016). This includes the use of information systems, visualisation tools and predictive analytics, underpinned by employee profiling and performance data.

The association of PA with HRM is obvious, given the emphasis on optimising recruitment, retention, assessment, promotion, remuneration, turnover and other aspects of human capital management. The Information Technology (IT) and cyber-security professions are also stakeholders, since data analytics are essential for red-flagging corporate threats, such as the misuse of organisational information, intellectual property theft or fraud (Guenole, Ferrar, & Feinzig, 2017). While these issues are important for all organisations, the potential value of automated techniques is magnified in those which are large and distributed, since traditional information needs and oversight mechanisms may exceed conventional HRM capabilities. Despite this potential, PA is still not well understood in the business or academic communities (Marler & Boudreau, 2017) beyond HR innovators, or in high-risk sectors such as defence and financial services, where such practices are often shrouded in commercial secrecy.

This scoping review aimed, through an analysis of online sources and academic literature, to better understand the nature, usage and potential of PA, as well as issues arising in the field. The specific objectives were to examine 1) the emergence of the PA concept over time

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and its relationship with other HR-related concepts 2) the contexts in which PA is being used; 3) the value propositions advanced by providers of PA products and services; and 4) training courses currently aimed at PA practitioners. The review was prompted by findings of a recent systematic literature review on HR Information Systems (HRIS) in healthcare, which highlighted the importance of HR data for effective management and organisational efficiency (Tursunbayeva, Bunduchi, Franco, & Pagliari, 2016). It complements a recent review of the academic research literature on HR Analytics (Marler & Boudreau, 2017) by extending the analysis to a wider set of knowledge types. It also addresses calls from within the industry for "independent scientific research" on PA (e.g. Julia Howes, quoted in Levenson & Pillans, 2017).

2. Methods

We undertook a quasi-systematic scoping review, adopting an approach originally proposed by Arksey and O'Malley (2005). Unlike systematic reviews aimed at synthesising evidence from evaluative studies (e.g. Tursunbayeva, Franco, & Pagliari, 2017), scoping reviews are often used to examine emerging topics that are poorly understood, where research is at an early stage, or where pertinent knowledge is being generated outside academia. Scoping reviews thus address broad rather than narrow research questions and seek to profile the literature and understand it holistically, rather than to critically appraise the methodological quality of individual studies (Holeman, Cookson, & Pagliari, 2016).

Since PA is an emergent topic it was appropriate to use this broad approach rather than concentrating on a narrow and likely unrepresentative academic research literature and specific and narrow research questions.

Data collection took place in four main phases, which are summarised below, noting the research objectives addressed by each one.

2.1. Mapping the use of PA-related terms online (Addresses objectives 1 and 2)

To inform our literature searches, we first created a draft set of ten keywords *[HR, Human Resource, People, Workforce, Employee, Human Capital, Manpower, Staff, Personnel, Talent],* drawing on the results of the recent systematic evidence review on HRIS in the context of healthcare (Tursunbayeva et al., 2016) and adding the word *"Analytics"* to each of these.

We analysed the prevalence of each of these keyword combinations in online searches, using Google Trends (searched on 10/06/2017), following previous research that uses this free tool to obtain insights on users' Internet search behaviour (e.g. Nuti et al., 2014).

We used additional Google Trends analytics to chart the *countries* in which each search term has been the most popular, as well as to examine the *related terms* used alongside PA in online searches in which PA keywords are included. Open coding (Glaser & Strauss, 1967) was applied to the latter to iteratively sort the results into thematic categories.

2.2. Scoping relevant academic research (Addresses objectives 1 and 2)

Using a subset of 7 core keywords refined after Phase 1 ("HR analytics" OR "Human Capital analytics" OR "Human Resource analytics" OR "People analytics" OR "Talent analytics" OR "Workforce analytics" OR "Employee analytics"), we undertook preliminary searches of the academic literature using the Scopus database (30/07/2017).

To check the *inclusivity* of our search results, the titles of articles judged to be relevant were cross-referenced with those appearing in two benchmark literature sources: Firstly, a recent review of academic research on HR Analytics by Marler and Boudreau (2017) which used similar search terms and shortlisted 14 relevant papers dating from 2004. Secondly, a list of relevant articles informally maintained by the Human Capital Analytics Group (HCA Group, 2017) of the Copenhagen Business School, encompassing 28 articles dating from 2002 (as of 30/07/2017).

The *disciplinary affiliation* of journals publishing PA research was assessed with reference to their classifiation in the Scimago Journal Ranking Portal (2017), except for the Scopus articles for which this information was available in the database. Where articles specified *keywords* these were cross-referenced with our seven search terms to identify those most frequently used. Finally, we analysed the *concepts* appearing in article titles and abstracts with reference to a framework by Isson and Harriott (2016) which organizes PA into 7 "pillars" according to its potential impact on: 1. Workforce planning; 2. Sourcing; 3. Acquisition/hiring; 4. Onboarding, culture fit, and engagement; 5. Performance assessment and development and employee lifetime value; 6. Churn and retention; and 7. Wellness, health, and safety.

2.3. Scoping commercial PA tools and services (Addresses objectives 2 and 3)

To identify venders of PA tools and services, we searched for each of our 7 core PA keywords in Google and analysed the first page of results for each one, based on previous studies showing that 91% of searchers check only this page (Van Deursen & van Dijk, 2009). For our analysis we included only the organic results (Ratliff & Rubinfeld, 2014), and omitted paid advertisements. The search was conducted on 30/07/2017.

Vendors identified from this search were first classified according to the *nature of their business*, using a taxonomy, developed by Libert, Beck, and Wind (2016), as Asset Builders; Service Providers; Technology Creators; Network Orchestrators. We then reviewed the narrarative in vendors' online promotional material, to identify the specified or implied benefits offered to prospective purchasers (*value proposition*). These were iteratively coded before settling on a refined list of benefit categories.

2.4. Scoping online training courses (Addresses objective 4)

Again, using the 7 keywords refined through Phase 1, we searched the Wikipedia list of massive online open courses (MOOC) by "Notable providers" (Wikipedia, 2017) (Search conducted on 30/07/2017). After examining the openly accessible information describing each course, we extracted those most closely related to PA and attempted to assess their *learning objectives*, insofar as this was possible without enrolling. These were cross-referenced with the "Profile of a Perfect Data Analyst" developed by the Nesta global innovation foundation (2014), which includes: Core skills (Analytical or Technical); Domain and Business Knowledge (Knowledge of the sector, Awareness of business goals and processes); Soft skills (Storytelling and Team-working) and Competencies (Analytics Mindset, Creativity and Curiosity). Available course content was also classified according to Isson and Harriot's 7 PA pillars framework, as described above. Finally, we emailed course developers and asked for the course creation date and attendance statistics.

3. Findings and analysis

3.1. People analytics in online search trends

None of the terms *Manpower Analytics, Personnel Analytics* or *Staff Analytics* were found in Google trends since records began in 2004. Although these terms appear in earlier articles included in a recent systematic review of HRIS (Tursunbayeva et al., 2016), their absence post-2004 suggests that they are no longer in common usage and we therefore decided to exclude them from further analysis. Indeed, these were also not found amongst the search terms or results in Marler and Boudreau's (2017) related review. The relative popularity of online searches for the remaining seven terms is shown in Fig. 1.

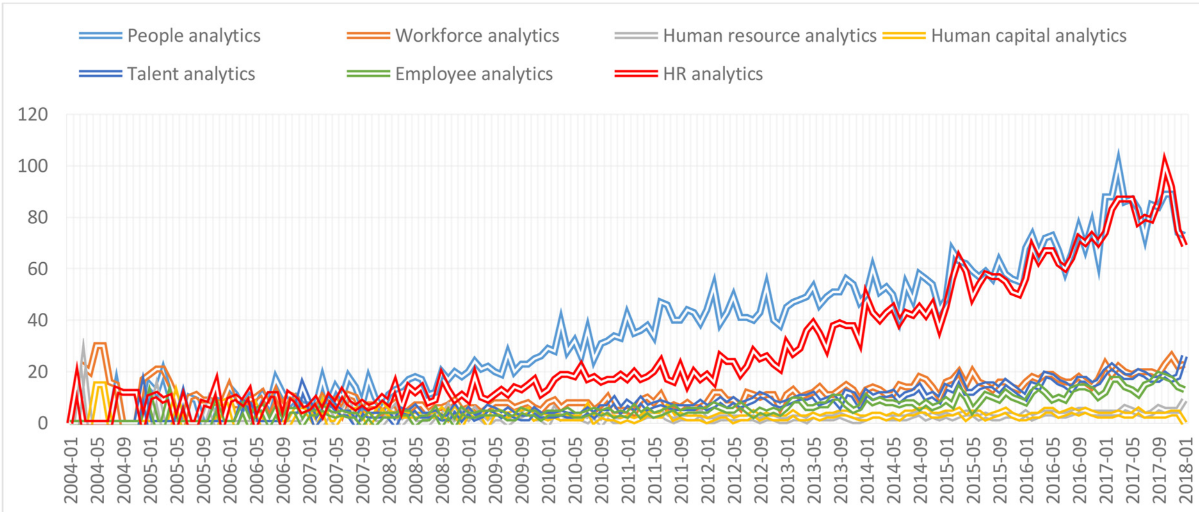

Fig. 1. Keyword utilization in Google Trends*.
*Google Trends data starts from 2004. Google Trends description: Numbers represent search interest relative to the highest point on the chart for the given region and time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. Likewise a score of 0 means the term was less than 1% as popular as the peak.

As can be seen in Fig. 1, interest in these terms has grown over the last fourteen years, with searches for *Human Resource*, *HR* and *Workforce Analytics* initially being the most popular. Google users began searching for *People Analytics* in 2005 and this term overtook the latter in 2007. In the last 10 years, the most popular terms have been *People Analytics* and *HR Analytics.* Searches for *Talent Analytics*, *Employee Analytics* and *Workforce Analytics* have also taken place, although relatively rarely compared with the former two search terms. Searches for *Human Capital Analytics* appeared and rose from 2004, although this term and *Human Resource Analytics* have since become the least popular of the seven reviewed.

Searches for PA concepts, recorded in Google Trends, were most popular in the USA, India, the UK, Australia and Canada, with users from the USA searching for the most diverse range of terms. Preferences for different search terms varied between countries. For example, the top search terms were, in the USA Human Capital Analytics, in India Talent Analytics and in Australia Workforce Analytics, while searches in the UK were more evenly spread across terms. Where relevant searches were conducted in other countries, these were confined to HR Analytics, People Analytics, or a combination of these two terms. A breakdown can be seen in Appendix A.

'Related words' used alongside the seven People Analytics search terms fell into several thematic clusters, based on our open coding (Appendix B). A cluster relating to ***HR objectives and practices*** was the most dominant - including aspects of workforce planning, recruitment, talent management and performance/reward. Related words from this cluster were mostly associated with the terms Human Resource, Human Capital and Talent Analytics. The next largest theme concerned ***Analytics*** as a class of methodologies, including predictive analytics or statistics. This was followed by a theme concerning *the **Internet***, including searches targeting particular social media platforms (e.g. Twitter), websites (e.g. Wordpress), search engines (e.g. Google search) or analytics engines (e.g. Google Analytics), which could potentially be used as a source of data for informing various HRM requirements. The Internet cluster seems to be unique to the People Analytics keyword, suggesting that the scope of the PA concept extends beyond internal HR processes and practices. The next category concerned ***Organisations,*** including references to companies in general or specific organisations offering PA services or technology, such as Deloitte (authors of the Human Capital Trends report). The PA keywords most closely associated with the Organisations category were Workforce and Talent Analytics. A further thematic category relates to the PA ***Profession*** – including descriptions of PA consultants, job advertisements or levels of remuneration. Other, less dominant, themes included ***Learning and Development***, (e.g. PA courses, training or academic programs), PA ***Research*** (both academic and applied), and ***Conferences*** *(Wharton School Univ. Pennsylvania)*. Finally, there was a cluster of searches related to PA in a particular ***Country***, specifically India.

3.2. People analytics in published academic research

3.2.1. Comparison of search results with 'benchmark' lists

Searching the Scopus database using a structured query combining our seven key terms yielded 58 relevant academic articles; almost all published in or after 2012. The table listing the included articles (after removing duplicates, and non-relevant returns: n = 5) is included in Appendix C together with the articles from the two 'benchmark' lists.

The two 'benchmark' lists did not have any article in common. Marler and Boudreau's review of academic research contains considerably more post-2012 articles than HCA group's list. Informal communication with the HCA group confirmed that their list is not systematically maintained but rather is a place to record articles of special interest. While our Scopus search identified more relevant articles than that shortlisted by Marler and Boudreau (58 vs. 14), only three of the same articles are covered in both reviews (by Aral, Brynjolfsson, & Wu, 2012; Bassi, 2011; Rasmussen & Ulrich, 2015). Fig. 2 shows the number of relevant articles appearing in our search and the two benchmark comparators, in the years 2002–2017.

3.2.2. Disciplinary focus

As can be seen in Fig. 3, while the majority of publications in all three sources come from the Business, Management and Accounting disciplines, the results from our Scopus search, Marler and Boudreau's academic literature review and the HCA group's list vary in several ways. Most significantly, technical disciplines such as the computing and mathematical sciences are strongly represented in Scopus and somewhat in Marler and Boudreau's lists but absent in the HCA group's list. The list derived from the HCA group, in contrast, shows a strong representation from Psychology. Interpreting these differences requires a recognition of the different scope and timeframes of the sources. Using our targeted search terms in Scopus yielded only studies published after 2008, whilst the HCA group's list goes back to 2002. Manual

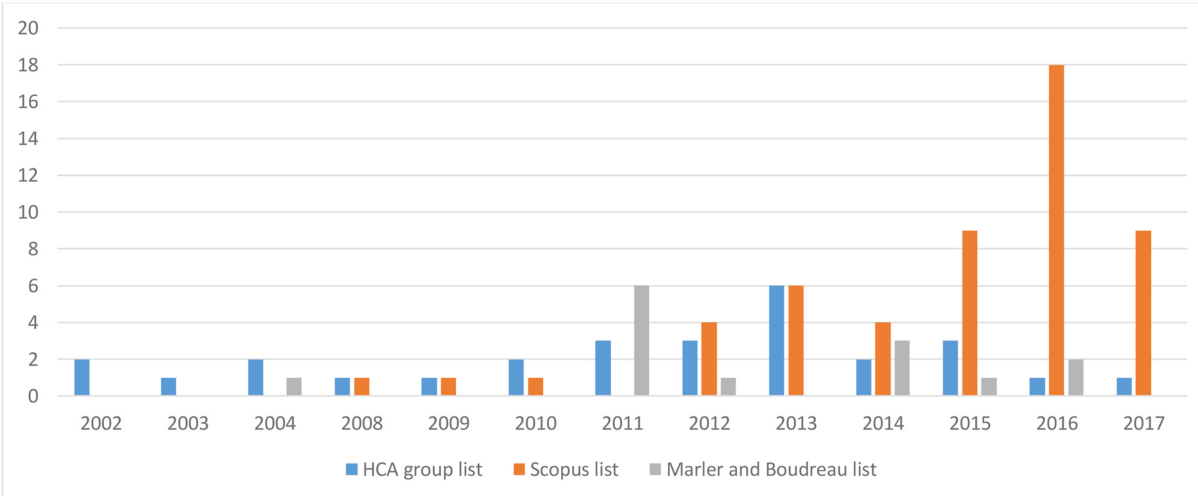

Fig. 2. Number of relevant articles appearing in search results and two benchmark sources, by publication date.

inspection of the pre- and post-2008 publications suggests that PA emerged from organisational psychology and psychometrics but has since been marked by a trend towards the computing and data sciences. Authors publishing most on this topic in the last five years come from industry, not academia; indeed one fifth of recent articles found in Scopus are affiliated with IBM, revealing the company's strategic shift towards business consulting and analytics. Nevertheless the difference between these sources partly reflects the addition of the word 'analytics' to the search terms in our Scopus search and Marler and Boudreau's review, compared to the HCA group's list.

3.2.3. Search terms and authors' keywords represented in published articles

The most popular keywords specified in articles derived from our Scopus search results were: Workforce Analytics; HR Analytics; Human Resource Management; People Analytics; and Human Resource Analytics. Not all articles in the HCA list specified keywords but where this was the case, these were divided between various *HRM practices* such as Diversity, Turnover, Engagement, Burnout, and Strategic HRM, and *organisational impacts* such as Organisational (or departmental) Performance, productivity or strategy. An additional keyword appearing in the this list was 'meta-analysis', reflecting the inclusion of review papers involving this method. The only keyword overlapping with our Scopus search terms was Human Capital, reflecting the focus of the HCA group. Very few articles in Marler and Boudreau's review of HR Analytics research used keywords. These keywords included: HR Analytics and Human Resource Analytics; Information Systems including Human Resource Information Systems; and generic HR terms such as Human Resource or Human Resource Management.

The keywords from all three lists were pooled to produce the word map shown in Fig. 4. The size of the words indicates their relative frequency.

Fig. 5 shows the annual frequency with which our core PA search terms, refined via phase 1, were specified as keywords by authors of academic articles in the combined list. Only five out of the seven terms are included, as Talent Analytics and Employee Analytics did not appear as keywords amongst these articles.

3.2.4. PA objectives/practices represented in the articles

Most of the articles in the combined list were general overviews or discussions of PA as an area of practice or a sub-discipline of HR. This included defining what PA is, its adoption rates in diverse organisations, types of data that may be used for PA analyses, and potential success factors and barriers that could affect PA implementation within organisations. While such generic PA articles appeared in our Scopus results and

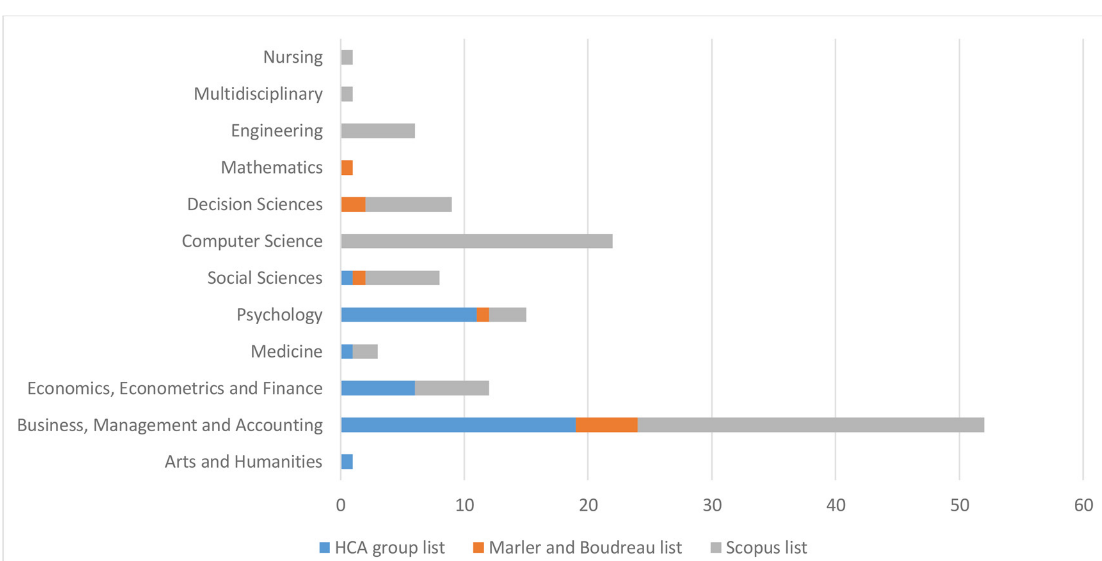

Fig. 3. Discipline of academic journals publishing articles related to People Analytics.

Fig. 4. Word map of keywords specified by authors.

in Marler and Boudreau's list, the HCA group's list only included studies focusing on the use of PA for specific HR objectives. Nevertheless, all of the PA objectives/practices from Isson and Harriott's (2016) 7 pillars framework were present in the studies analysed, as described in Table 1. Many focused on *performance assessment and development* and *employee lifetime values* (e.g. remuneration levels for different gender groups) and *on-boarding, culture fit, and engagement* (e.g. linking motivational antecedents, strategic implementation and company performance). Another dominant category, primarily in the studies found in Scopus, is *workforce planning*, including studies concerned with new scheduling models or identifying and estimating employee expertise. Other studies focused on the use of PA for: *churn and retention* (e.g. employee turnover and their impact); *wellness, health, and safety* (e.g. strategies for reducing employee burnout); *sourcing* (e.g. identifying key metrics to evaluate talent acquisition strategies or recruitment channels); and *acquisition/hiring* (e.g. evaluating potential biases using data mining and profiling tools during candidate screening).

Studies that did not belong to any of the aforementioned categories were grouped into separate categories. These included studies that focused on: *collaborations* (e.g. studying work patterns from employees' collaboration activities); *diversity and inclusion* (e.g. understanding how demographic factors and workforce composition can affect individual, team or organisational performance); *People Risks* (e.g. quantifying human risks and reviewing existing risk measures); and *inter-organisational relationships* (e.g. investigating how PA can be used in investment processes).

3.3. PA vendors represented in Google search results

As described in the methods section, we analysed the results appearing on the first Google page found when searching for each of our 7

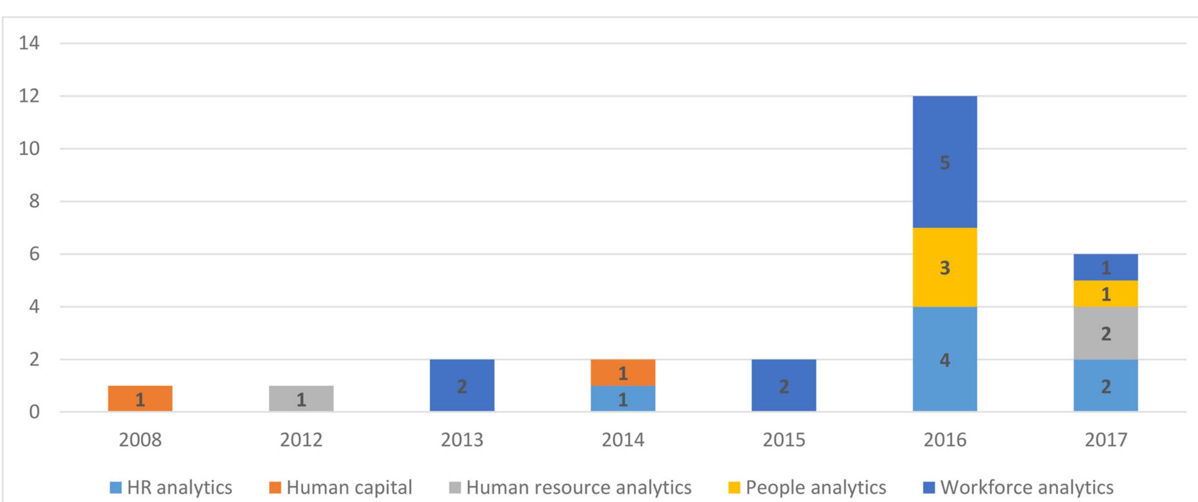

Fig. 5. Frequency of Specfied Keywords in PA-Related Journal Articles Over Time.

Table 1
PA objectives described in studies yielded by the Scopus search, HCA group list, recent review[a].

Study focus	Scopus list	HCA group list	Marler and Boudreau list
Workforce planning	9	–	–
Sourcing	2	–	–
Acquisition/hiring	1	–	–
Onboarding, culture fit, and engagement	1	13	1
Churn and retention	1	6	–
Wellness, health, and safety	–	6	–
Performance assessment and development and employee lifetime value	8	5	1
Diversity and inclusion	1	6	–
Collaboration	2	–	–
People Risks	1	–	–
Inter-organisational relationships	2	–	–
Generic, Technical or too little info to classify	25	–	12

[a] Some articles focused on more than one HR objective/practice.

core keywords, after removing paid advertisements. Most search results were links to *Vendor* websites (e.g. IBM's HR Analytics main page). The remaining results related; in order of frequency; to *News* (e.g. Forbes), *Research* (e.g. Harvard Business Review), PA-related *Communities* (e.g. Kaggle), *Organisations/Platforms* providing access to educational materials on PA (e.g. HCA Group webpage, Coursera) or specific training programmes in which PA is a component (e.g. Human Resources MBA), and *Conferences* (e.g. Wharton people analytics conference).

Terms used by vendors: Many vendors' websites contained several PA-related terms, although these varied in emphasis and frequency. Examples include, *"We'll show you how to build your* ***Talent Analytics*** *solutions. Point solutions demonstrate ROI of* ***people analytics*** *to the business"* (PWC, 2017), "***People analytics, also known as talent analytics*** *or* ***HR analytics****, refers to the method of analytics that can help managers and executives make decisions about their* ***employees or workforce****"* (Cornerstone, 2018). Here, we also identified an additional PA-related term ***"Labor Analytics"****,* used by Kronos, which did not emerge in the previous phases of analysis. Further details of vendors' descriptions and the definitions they follow are provided in Appendix D.

Stated value proposition: The following overlapping categories of promised benefit emerged from the qualitative analysis of vendors' online marketing narratives: (A) *Better strategic decision making* through access to reliable information and analytical tools; (B) *Improved data handling processes* using innovative approaches to data collection, combination, analysis and interpretation; (C) *Improved people management* resulting from greater efficiencies and HR decision making; (D) *New technological solutions* for collecting, storing or analysing HR data, including automating these processes; (E) *Direct impacts on HR or strategic business outcomes,* such as optimising human resource assets to increase income relevant to payroll; and (F) *Employee-oriented benefits* such as improved work experience or job satisfaction. Companies that appeared amongst the relevant web pages, but only provide business-to-business marketing services to PA vendors (e.g. TechTarget), were not included in this analysis.

We mapped the vendors according to their types, terminologies and stated value propositions, to produce the PA landscape map shown in Table 2.

3.4. People analytics courses

After searching the Wikipedia list of MOOC by "Notable providers" (2017) we identified three with one or more of our keywords in their title. Two explicitly include the term PA, – both originating from universities, one in Russia and one in the USA. The other, developed by a Canadian consulting firm, uses the term HR Analytics.

All three are introductory-level courses, explaining how PA can be used for diverse HRM practices (see Table 3). Each covers different types of HR data and the various ways in which it can be analysed (*Knowledge of the Sector*) to achieve diverse organisational objectives (*Awareness of Business Goals and Processes*). Categorizing the curricula according to the 7 PA pillars framework (Isson & Harriott, 2016), revealed that the two courses specifically focused on PA covered cases related to *Performance and development and lifetime value, Onboarding, culture fit, and engagement, Workforce planning,* and *Acquisition/hiring. Collaboration* emerged as a separate theme, and is described in the course syllabus as "principles behind using PA to improve collaboration between employees inside an organisation so they can work together more successfully" (People Analytics course, Massey, Haas, & Bidwell, 2017).

Table 2
Vendors classified according to PA-concepts and categories of value proposition.

Vendors	Value Proposition	Workforce Analytics	Employee Analytics	HR Analytics	Human Resource Analytics	People Analytics	Human Capital Analytics	Talent Analytics	Labor Analytics
Deloitte	A; B; C	+		+		+	+	+	
Competitive Analytics	A; B; C		+						
IBM[a]	A; B; C; E; F			+	+				
McKinsey & Company	B; C; E					+			
Accenture	A; B; C; D; E; F						+		
PWC	A; B; E							+	
Technology creators									
Kronos	A; B; C; D; E	+							+
SAP SuccessFactors[a]	A, D, E	+	+						
Talent Analytics	B; D; E	+						+	
Ultimate Software	A; B; D; E	+							
Visier	A; C; D	+	+						
QuestionPRO	D; E; F		+						
Talent LMS	A; C		+						
Cornerstone	A; B; C; D; E					+		+	
Network orchestrators									
TechTarget				+	+				

[a] Both service provider and technology creator.

4. Discussion

The results of our scoping review demonstrate the emergence of the term People Analytics and related concepts over the last 15 years, both within academic research and in online searches. They also delineate the value propositions stated by PA vendors and summarise the core training objectives of PA MOOC.

4.1. Terminological trends

Our analysis of the PA-associated terms used in academic sources and in Google searches reveals an evolving and diversifying field originating in the traditional HRM profession (historically influenced by industrial psychology), through a critical period of innovation in digital infrastructure, technologies and analytical capabilities, reflecting broader trends in the digital economy over the period studied. A range of relevant terms were already being used to search Google when records began in 2004, including Workforce Analytics, Human Resource and HR Analytics, although the latter terms only started appearing as keywords in academic articles from 2012. Human Capital was the first of our keywords to appear amongst the academic articles (in 2008). Academic articles specific to PA emerged only in the last two years and this is now the most popular of the relevant terms according to Google Trends, closely followed by HR Analytics. In practice, many of these terms are being used interchangeably, both by academics and vendors, although some practitioners align HR analytics with conventional HR and PA with a broader range of enterprise-level and strategic analytics (Van Vulpen, 2016). Google searches for one or more of our key terms took place in as many as 13 countries, with preferences for different search terms differing between regions (Our analysis of 'Related words' in Google queries also revealed a cluster of searches related to PA in India, which may be attributable to online activity surrounding the HR Analytics India Summit 2017) Among academics, the most commonly used terms were Workforce- HR-, People-, and Human Resource- Analytics, while vendor websites show a preference for Workforce-, Employee- and Talent- Analytics.

Changes in terminology over time reflect the evolution of the HR field, from conventional personnel management functions (e.g. payroll), towards the greater use of IT systems and data for strategic purposes such as workforce planning (e.g. Haines & Lafleur, 2008). They also suggest a re-branding of similar concepts by successive practitioner cohorts and vendors, as they seek to differentiate their knowledge, services or products in a competitive market. Elements of both the changing focus and rebranding of concepts can be seen in the recent appearance, both in academic papers and MOOC, of the concept of *Collaboration or Relationship Analytics,* reflecting the growing use of social media or organisational network analysis (see Objectives of PA).

4.2. Affiliation and disciplinary focus

Echoing a recent systematic review on HR Analytics (Marler & Boudreau, 2017), we observed that the authors of most published articles on PA came from consulting or technology companies. This trend has also been reported in previous research on HRIS, in which consultancy firms feature prominently (Ruel & Bondarouk, 2008). Most of the academic articles and PA courses included in our review approach PA as a sub-field of HR, which was also reflected in the headline curricula of the three MOOC. Nevertheless, our analysis shows that research in this area is highly interdisciplinary. While most articles come from the Business, Management and Accounting domains, social science has remained prominent, and the importance of the computing and data sciences is increasingly evident, echoing the growth of HRIS and digital innovations for monitoring, evaluating and predicting work.

4.3. Objectives of PA

The most popular objectives and practices, based on Isson and Harriot's 7 pillars model, were *performance assessment and development* and *employee lifetime values*; *onboarding, culture fit, and engagement,* and *workforce planning*. Our thematic analysis yielded four additional categories – *employee collaborations; diversity and inclusion; people risk*s, and *inter-organisational relationships*. The emergence of these categories illustrates the rapid development and diversification of the field, as already discussed with reference to terminologies and disciplines. One example is the shift in emphasis from HR practices focused on individuals, to their interactions, affiliations and performance as groups, including the use of data on social and organisational networks. The significance of this shift has recently been highlighted in a report by Bersin for Deloitte (2016), who predicts that *relationship analytics* will soon come to replace traditional organisational design/re-design approaches. An increasing emphasis on measuring *people risks* (Marsh Risk Consulting, 2017) via analytics is also noteworthy, including not only conventional risks such as staff attrition, organisational reputation or customer safety, but also new forms of cyber-risk for which these new methods are well-suited, such as hack vulnerability or data theft (e.g. Royal & Windsor, 2016). Other recent trends include the use of linked employee data and analytics as a substitute for conventional psychometric testing in the acquisition and management of talent (indeed, the term PA was historically used to describe this sort of test-based employee profiling). One market indicator of this emerging trend, is the recent acquisition of psychometric assessment specialists Cut-e by AON, a global professional services firm that uses data and analytics to help companies manage workforce risks, health and retirement (Consultancy.uk, 2017).

4.4. Business value offered by PA

All of the companies identified through our online searches are either service providers or technology creators. Providers of PA services typically offer strategic and operational consulting aimed at improving the collection, management and use of data for understanding and evaluating work behaviour or outcomes and optimising human resources. PA technology vendors offer IT systems for achieving these aims by making workforce intelligence and predictive analytics more accessible, thus supporting strategic decision making and improving *business outcomes,* reflecting the vision of 'actionable analytics' (Dykes, 2016). Cross-referencing vendors' stated solutions with the coded articles in our review revealed some overlap in vision and intentions, but little evidence of the benefits promised. Thus, while business analysts are promoting new ways of creating measurable organisational impacts through PA, objective academic research is needed to evaluate these.

4.5. PA skills being sought

An indicator of how companies are actively seeking value from PA can be seen in the MOOC we analysed, including the market leader in PA training (Wharton Business School). The fact that we were able to identify only three such courses, only one of which was explicitly labelled as "People analytics", suggests that the supply of training is far from sufficient to meet the need for relevant skills amongst HR professionals. Nevertheless, the increasing inclusion of PA within university curricula on business and management (e.g. the HR Analytics and Research course from the University of Denver, USA), along with new programmes in data science (e.g. the MSc in Data Science, Technology and Innovation from the University of Edinburgh, UK), and the emergence of other relevant online courses (e.g. People Analytics training with Gene Pease) will go some way towards addressing this deficit. In the meantime, the growth in professional conferences focused on PA (e.g. the Wharton People Analytics Conference or HR Analytics

Table 3
Massive Online Open Courses focused on People Analytics[a].

Course name	Source	Instructors	Affiliation	Pre-requisites	Syllabus	PA Pillars	Learners
Introduction to People Analytics	Coursera	Alexey Dolinskiy and Ilya Breyman (Adjunct Professors)	Center of Innovative Educational Technologies, Moscow Institute of Physics and Technology, Russia	N/A	7 Weeks: Introduction, Performance, Culture and Assessments, Compensation, Motivation & Engagement, Workforce Planning & Recruitment, Development	-Performance and development and lifetime value -Onboarding, culture fit, and engagement -Workforce planning -Acquisition/ hiring	Info on learners not available
People Analytics. Part of the Business Analytics specialization. (launched December, 2015)	Coursera	Cade Massey (Practice Professor), Martine Haas, Matthew Bidwell (Associate Professors of Management)	The Wharton School, University of Pennsylvania, USA	N/A	4 Weeks: Introduction to People Analytics & Performance Evaluation, Staffing, Collaboration, Talent Management & Future Directions	-Performance and development and lifetime value -Workforce planning -Collaboration	2015: 11,599 2016: 26,312 2017: 49,535 (71% male; 29% female) US = 26%; India = 18; remaining countries all with < 4%
The Fundamentals of HR Analytics (launched March, 2016)	Udemy	David Creelman, CEO	Creelman Research, Toronto, Canada	Practicing HR professionals	17 short videos covering what HR Analytics is, and success factors and barriers to keep in mind in development and execution of HR Analytics projects	N/A	Circa 150 students

[a] Differences in specification reflect the availability of information online for the three courses.

India Summit 2017) indicates the desire, primarily amongst international HR professionals, to fill this gap. The establishment of a new "HR Analytics Academy" in 2016 in the Netherlands, also suggests that these 'advanced' approaches will soon be finding their way into routine HR practices.

4.6. Working definition

In their recent review, Marler and Boudreau (2017) summarise HR analytics as: *"An HR practice enabled by information technology that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organisational performance, and external economic benchmarks to establish business impact and enable data-driven decision making"*. While our broader scoping analysis reveals similar objectives, we note that vendors such as Accenture, IBM and QuestionPRO have begun to extend this to improvements in employee experience and satisfaction. Indeed, employee experience was identified as key priority for future HR in the latest Deloitte (2017) report, which states: *"The concept of 'total employee experience', focused on design thinking and the simplification of work, will become a major focus in HR"*. Thus, based on our study, we would offer the following definition of People Analytics *"People Analytics is an area of HRM practice, research and innovation concerned with the use of information technologies, descriptive and predictive data analytics and visualisation tools for generating actionable insights about workforce dynamics, human capital, and individual and team performance that can be used strategically to* optimise *organisational effectiveness, efficiency and outcomes, and improve employee experience"*.

5. Conclusions, caveats and recommendations

Scoping reviews are exploratory research exercises and the intention here was to provide insights about this emerging area by mapping the terms, concept and practices associated with PA, rather than to provide an in-depth analysis of PA innovations, professions, markets or research. The results nevertheless indicate the direction of developments and the increasing readiness of PA to embrace new innovations and market demands. Given the rapid pace of technological change, this represents only a snapshot of the field to date.

One purpose of scoping reviews is to inform the design of future systematic reviews by testing and refining literature search strategies. Here, this enabled us to identify a more comprehensive set of search terms than we had previously been aware of and showed that focusing on activities explicitly described as 'analytics' is no guarantee of revealing the diversity of the domain. It also demonstrated the importance of widening searches beyond academic databases to uncover relevant grey literature, and of including emerging terms such as "Human Capital Data", "Human Resource data", "Talent data", "Workforce data", "Analytics in HR", "HR metrics", "HR predictive analytics", "Collaboration Analytics", "People Intelligence", "Labor Analytics" and "Relationship Analytics". The diversity of disciplines represented amongst academic and online sources of PA insights also suggests that scholars and practitioners interested in this topic should look beyond the HR or management literature for relevant studies, including in specialist sectors where PA is being applied, such as banking, security or healthcare, and examine real-world applications in addition to academic research.

The first page of Google results arising from each key search term provides only a snapshot of the vendor ecosystem. Deeper, iterative web searches, and consultation exercises with PA experts would be valuable for understanding the 'analytic maturity' of organizations in diverse sectors, drawing on existing frameworks (e.g. Lismont, Vanthienen, Baesens, & Lemahieu, 2017; Grossman, 2018), as well as for elucidating the changing business demands for PA and identifying PA services not represented online.

Finding so few empirical studies leads us to join other reviewers in calling for more academic research in this area, including evaluation studies, case studies of PA implementation and simulation studies exploring the potential outcomes of new PA models before they are implemented, as well as to examine the nascent introduction of machine learning and Artificial Intelligence in the context of workforce management (Meister, 2017).

Amongst the wide variety of sources examined, we noted a marked absence of ethical considerations in relation to PA practices, some of which are covert or reach beyond the boundaries of organisations themselves. Examples include the monitoring of personal social media or email activity, which have implications for privacy, the use of algorithmic decision making for recruitment or promotion, which has potential to introduce bias and discrimination, and the digital abstraction of personality and ability profiles from real world data without the need for psychometric testing, which raises issues for transparency and consent (Wiedemann, 2018). With advances in privacy regulations, such as recently enforced European General Data Protection Directive, PA practitioners may soon have to re-think some of these approaches. Although lawyers, ethicists and management scientists are already addressing some of these issues (e.g. Bodie, Cherry, McCormick, & Tang, 2017; Dagnino, 2017; Pasquale, 2015), our observations suggest that this is a blind spot for the PA profession itself and we recommend further research to understand how practitioners, vendors and employers are reconciling the drive for innovation with requirements for transparency and accountability. Ethics in PA will be the focus of a special Professional Development Workshop at the 2018 British Academy of Management Conference, which also draws on this review (Pagliari, Tursunbayeva, & Antonelli, 2018).

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Appendix A. Relative popularity of keywords in individual countries (from Google Trends)*

Country	UK	USA	India	Australia	Canada	Other countries
HR Analytics	20	20	68	21	20	Singapore (100) Netherlands (59) Brazil (2) Germany (10) Spain (8) UAE (40) Philippines (30)
People Analytics	51	44	27	43	50	Singapore (100) Netherlands (40) South Africa (27) Brazil (19) Germany (17) Spain (11) Poland (3)
Workforce Analytics	53	83	46	100	75	–
Talent Analytics	49	88	100	–	–	–
Human Capital Analytics	–	100	–	–	–	–
Employee Analytics	–	–	–	–	–	–
Human Resource Analytics	–	–	–	–	–	–

* Google Trends description: Values are calculated on a scale from 0 to 100, where 100 is the location with the most popularity as a fraction of total searches in that location, a value of 50 indicates a location which is half as popular, and a value of 0 indicates a location where the term was less than 1% as popular as the peak. Note: A higher value means a higher proportion of all queries, not a higher absolute query count, so a tiny country where 80% of the queries are for "bananas" will get twice the score of a giant country where only 40% of the queries are for "bananas".

Appendix B. Related words used in searches for People Analytics terms (Google trends, searched on June 16, 2017)*

Related topics	Employee analytics	HR Analytics	Human Capital Analytics	Human resource analytics	People Analytics	Talent Analytics	Workforce Analytics
HR Objectives/ Practices							
Employee benefits	10						
Employment	100	5		10			5
Human capital			100	5			
Human resource management		10	5	45		5	5
Human resource management system				10			
Human Resources	15	100	25	100	5	30	20
Workforce	5	5	10	10		10	95
Workforce management							5
Workforce planning							15

Turnover	5						
Recruitment	5	5		5		20	5
Talent management						25	
Management	10	5	15	15		5	5
Marketing			5			5	
Measurement			5				
Performance metric		5	5			5	5
Strategy	5		5			5	5
Index term					5		
Churn rate	5						
Analytics							
Analysis	5			5	5		5
Analytics	70	95	95	95	50	100	100
Big data	5	5	5	5	5	10	5
Data	5	5			5	5	5
Data analysis	10	10	5	10	5	10	5
Business analytics	5	5	5	15	5	5	
Predictive analytics	5	5	5	5		10	5
Statistics					5		
Internet							
Twitter					10		
Website					25		
WordPress					5		
Blog					5		
LinkedIn	5	5	5		5	10	
Google Analytics	45	15	5	15	100	45	5
Google Search					5		
Web analytics					5		
Advertising					5		
AdWords					5		
Organisations							
Deloitte			5			5	5
IBM	5					5	5
Company	10	5	5	5	5	10	5
Oracle Corporation		5					
Organization			5	5			
SAP SE							5
Service							
Software	5			5			5
SuccessFactors							10
Technology						5	
Profession							
Consultant			5			5	
Career				5		5	
Job	10	10	5	10		15	5
People					5		
Salary	10	5	5	5			
Learning and Development							
Course		5		5			
How-to					35		
Master's Degree				5			
Training		5					5
Research							
Research				5			
Review	10						
User					5		
Microsoft PowerPoint		5					
Portable Document Format				10			
Conferences							
Wharton School Univ. Pennsylvania					5		
Country							

India	5	5

*Related topics in Google Trends defined as “users searching for your term also searched for these topics”. Includes results for the most popular topics (or Top): Scoring is on a relative scale where a value of 100 is the most commonly searched topic, a value of 50 is a topic searched half as often, and a value of 0 is a topic searched for less than 1% as often as the most popular topic.

Appendix C. Analysed articles from Scopus, HCA group, and Marler and Boudreau lists

N	Reference	Journal Discipline	Keywords used	PA objective
Scopus List				
1.	Angrave, D., Charlwood, A., Kirkpatrick, I., Lawrence, M., & Stuart, M. (2016). HR and analytics: why HR is set to fail the big data challenge. *Human Resource Management Journal*, 26(1), 1–11.	- Business, Management and Accounting	- HR analytics - Human resource information systems - Big data	- Generic
2.	Aral, S., Brynjolfsson, E., & Wu, L. (2012). Three-way complementarities: Performance pay, human resource analytics, and information technology. *Management Science*, 58(5), 913–931.	- Business, Management and Accounting - Decision Sciences	- Human Resource Analytics - Incentive systems - Information technology - Performance pay - Production function - Principal-agent model - Complementarity - Enterprise systems - ERP - Productivity	- Performance assessment and development and employee lifetime values
3.	Baesens, B., De Winne, S., & Sels, L. (2017). Is your company ready for HR analytics? *MIT Sloan Management Review*, 58(2), 20–21.	- Business, Management and Accounting - Decision Sciences	- N/A	- Generic
4.	Bassi, L., & McMurrer, D. (2016). Four Lessons Learned in How to Use Human Resource Analytics to Improve the Effectiveness of Leadership Development. *Journal of Leadership Studies*, 10(2), 39–43.	- Social Sciences	- N/A	- Performance assessment and development and employee lifetime values
5.	Chiappinelli, C. (2009). HCM complexity rises in global setups. *Managing Automation*, 24(11), 35–37.	- Business, Management and Accounting - Decision Sciences - Engineering	- N/A	- Generic
6.	Davenport, T. H., Harris, J., & Shapiro, J. (2010). Competing on talent analytics. *Harvard Business Review*, 88(10), 52–58, 150.	- Business, Management and Accounting - Economics, Econometrics and Finance	- N/A	- Generic
7.	Dessain, N. (2016). Human resources marketing and recruiting: Introduction and overview. In *Handbook of Human Resources Management* (pp. 3–22).	- Business, Management and Accounting - Economics, Econometrics and Finance	- Recruiting - Recruitment - Recruitment marketing - Staffing - Talent acquisition - HR marketing	- Sourcing
8.	Dexter, F., Ledolter, J., & Hindman, B. J. (2016). Quantifying the Diversity and Similarity of Surgical Procedures among Hospitals and Anesthesia Providers. *Anesthesia and Analgesia*, 122(1), 251–263.	- Medicine	- N/A	- Diversity and inclusion
9.	Dong, S., Johar, M., & Kumar, R. (2013). Workforce analytics for knowledge-intensive service delivery using a private service marketplace. In *WITS 2013 - 23rd Workshop on*	- Computer Science	- N/A	- Generic

	Information Technology and Systems: Leveraging Big Data Analytics for Societal Benefits.			
10.	Dubey, A., Abhinav, K., Taneja, S., Virdi, G., Dwarakanath, A., Kass, A., & Kuriakose, M. S. (2016). Dynamics of software development crowdsourcing. In Proceedings - *11th IEEE International Conference on Global Software Engineering, ICGSE 2016* (pp. 49–58).	- Business, Management and Accounting - Computer Science	- Workforce analytics - Software development - Tracking - Forecasting - Crowdsourcing	- Performance assessment and development and employee lifetime values
11.	Fang, D., Varshney, K. R., Wang, J., Ramamurthy, K. N., Mojsilovic, A., & Bauer, J. H. (2013). Quantifying and recommending expertise when new skills emerge. In Proceedings - *IEEE 13th International Conference on Data Mining Workshops, ICDMW 2013* (pp. 672–679).	- Computer Science	- Workforce analytics - Expertise taxonomy - Recommendation systems - Enterprise social networks - Cold-start problem	- Performance assessment and development and employee lifetime values
12.	Fecheyr-Lippens, B., Schaninger, B., & Tanner, K. (2015). Power to the new people analytics. *McKinsey Quarterly*, (1).	- Business, Management and Accounting - Economics, Econometrics and Finance - Social Sciences	- N/A	- Generic
13.	Ghosh, S., Zheng, Y., Lammers, T., Chen, Y. Y., Fitzmaurice, C., Johnston, S., & Li, J. (2016). *Deriving public sector workforce insights: A case study using Australian public sector employment profiles* (Vol. 10086 LNAI).	- Computer Science - Engineering	- Workforce analytics - Public sector - Data mining	- Generic
14.	Hausknecht, J. (2013). Workforce Analytics. In *Workforce Asset Management Book of Knowledge* (pp. 367–392).	- Business, Management and Accounting	- Workforce analytics - Benchmarking - Data collection systems - Workforce asset management (WAM) - Workforce management (WFM) - Workforce management professional (WAM-Pro)	- Generic
15.	Horesh, R., Varshney, K. R., & Yi, J. (2016). Information retrieval, fusion, completion, and clustering for employee expertise estimation. In Proceedings - *2016 IEEE International Conference on Big Data, Big Data 2016* (pp. 1385–1393).	- Computer Science	- Workforce analytics - Unsupervised learning - Human talent management	- Workforce planning
16.	Kapoor, B., & Kabra, Y. (2014). Current and future trends in human resources analytics adoption. *Journal of Cases on Information Technology*, 16(1), 50–59.	- Business, Management and Accounting - Computer Science - Decision Sciences	- Human capital - HR metrics - Return on investment - Business intelligence - Predictive and prescriptive analytics - Analytics Maturity Model - Descriptive	- Generic
17.	Khan, S. A., & Tang, J. (2016). The paradox of human resource analytics: Being mindful of employees. *Journal of General Management*, 42(2), 57–66.	- Business, Management and Accounting	- N/A	- Generic
18.	King, K. G. (2016). Data Analytics in Human Resources: A Case Study and Critical Review. *Human Resource Development Review*, 15(4), 487–495.	- Business, Management and Accounting	- Strategic HRM - Retention - HRD management - HR practices	- Generic
19.	Lal, P. (2015). Transforming hr in the digital era: Workforce analytics can move people specialists to the center of decision-making. *Human Resource Management International Digest*, 23(3), 1–4.	- Business, Management and Accounting	- Human resource management - Information management	- Generic

		- Organizational performance - Decision-making	
20. Lismont, J., Vanthienen, J., Baesens, B., & Lemahieu, W. (2017). Defining analytics maturity indicators: A survey approach. *International Journal of Information Management*, 37(3), 114–124.	- Computer Science - Social Sciences	- Analytics techniques - Organizational characteristics - Survey research - Analytics maturity	- Generic
21. Mankins, M., Brahm, C., & Caimi, G. (2014). Your scarcest resource. *Harvard Business Review*, 92(5), 74–80, 133.	- Business, Management and Accounting - Economics, Econometrics and Finance	- N/A	- Collaboration
22. Marler, J. H., & Boudreau, J. W. (2017). An evidence-based review of HR Analytics. *International Journal of Human Resource Management*, 28(1), 3–26.	- Business, Management and Accounting	- Human resource analytics - Talent management - Strategic HRM - HRIS - HR metrics - Workforce analytics	- Generic
23. Martin-Rios, C., Pougnet, S., & Nogareda, A. M. (2017). Teaching HRM in contemporary hospitality management: a case study drawing on HR analytics and big data analysis. *Journal of Teaching in Travel and Tourism*, 17(1), 34–54.	- Business, Management and Accounting - Social Sciences	- HR analytics - Hospitality education - Human resource management - Teaching guide - Case method - Big data analysis	- Generic
24. Mashhadi, A., Acer, U. G., Boran, A., Scholl, P. M., Forlivesi, C., Vanderhulst, G., & Kawsar, F. (2016). Exploring space syntax on entrepreneurial opportunities with Wi-Fi analytics. In *UbiComp 2016 - Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (pp. 658–669).	- Computer Science	- People analytics - Space syntax - Network sensing	- Inter-organisational relationships
25. Momin, W. Y. M., & Mishra, K. (2014). Impression of financial measures in HR analytics. *Journal of Interdisciplinary and Multidisciplinary Research*, 2(1), 87–91.	- Multidisciplinary	- HR analytics - Human resource management - Predictive analytics - Financial measures	- Generic
26. Natesan Ramamurthy, K., Varshney, K. R., & Singh, M. (2013). Quantile regression for workforce analytics. In *2013 IEEE Global Conference on Signal and Information Processing, GlobalSIP 2013 - Proceedings* (p. 1134).	- Computer Science	- Productivity profile - Quantile regression - Workforce behavior - Attrition profile	- Churn and retention
27. Nienaber, H., & Sewdass, N. (2016). A reflection and integration of workforce conceptualisations and measurements for competitive advantage. *Journal of Intelligence Studies in Business*, 6(1), 5–20.	- Business, Management and Accounting - Decision Sciences	- Workforce analytics - Predictive analytics - Strategy - Workforce - Organisational performance - Workforce intelligence - Workforce metrics - Competitive advantage	- Generic
28. Ozgur Bayman, E., Dexter, F., & Ledolter, J. (2017). Mixed effects logistic regression modeling of daily evaluations of nurse anesthetists' work habits adjusting for leniency of the rating anesthesiologists. *Perioperative Care and Operating Room Management*, 6, 14–19.	- Medicine - Nursing	- Human resource analytics - Mixed effects logistic regression - Performance evaluation - Anesthesiology	- Performance assessment and development and employee lifetime values
29. Palshikar, G. K., Pawar, S., & Ramrakhiyani, N. (2016). Role models: Mining role transitions data in IT project management. In Proceedings - *3rd IEEE International*	- Computer Science - Decision Sciences	- HR Analytics - Project Management - Role-based Teams - Sequence Mining	- Workforce planning

Conference on Data Science and Advanced Analytics, DSAA 2016 (pp. 508–517).		- Survival Analysis - Workforce Management - Graph Clustering - Classification	
30. Palshikar, G. K., Sahu, K., & Srivastava, R. (2015). *After you, who? Data mining for predicting replacements* (Vol. 9468).	- Computer Science - Engineering	- N/A	- Workforce planning
31. Persson, A. (2016). Implicit Bias in Predictive Data Profiling Within Recruitments. In A. Lehmann, D. Whitehouse, S. Fischer-Hübner, L. Fritsch, & C. Raab (Eds.), *Privacy and Identity Management. Facing up to Next Steps: 11th IFIP WG 9.2, 9.5, 9.6/11.7, 11.4, 11.6/SIG 9.2.2 International Summer School, Karlstad, Sweden, August 21-26, 2016*, Revised Selected Papers (pp. 212–230). Cham: Springer International Publishing.	- Decision Sciences	- People analytics - Discrimination - Implicit bias - Machine-learning - Recruitment - Social exclusion - Big Data	- Acquisition/Hiring
32. Bassi, L. (2012). Raging debates in HR analytics. *Human Resource Management International Digest*, 20(2), 74–80.	- Business, Management and Accounting	- N/A	- Generic
33. Ramamurthy, K. N., Singh, M., Davis, M., Kevern, J. A., Klein, U., & Peran, M. (2016). Identifying Employees for Re-skilling Using an Analytics-Based Approach. In Proceedings - *15th IEEE International Conference on Data Mining Workshop, ICDMW 2015* (pp. 345–354).	- Computer Science - Engineering	- Workforce analytics - Skill adjacency - Skills taxonomy - Human resource - Employee training	- Performance assessment and development and employee lifetime values
34. Rasmussen, T., & Ulrich, D. (2015). Learning from practice: How HR analytics avoids being a management fad. *Organizational Dynamics*, 44(3), 236–242.	- Business, Management and Accounting - Psychology - Social Sciences	- N/A	- Generic
35. Royal, C., & O'Donnell, L. (2008). Emerging human capital analytics for investment processes. *Journal of Intellectual Capital*, 9(3), 367–379.	- Business, Management and Accounting - Social Sciences	- Human capital - Financial markets - Hong Kong - Intangible assets - Financial institutions - Australia	- Inter-organisational relationships
36. Royal, C., & Windsor, G. S. S. (2016). Sustainable institutional investment models and the human capital analytics approach: A great gap to be filled. In *Routledge Handbook of Social and Sustainable Finance* (pp. 431–447).	- Business, Management and Accounting - Economics, Econometrics and Finance	- N/A	- People risks
37. Ryan, J., & Herleman, H. (2016). A big data platform for workforce analytics. In *Big Data at Work: The Data Science Revolution and Organizational Psychology* (pp. 19–42).	- Psychology	- N/A	- Generic
38. Shami, N. S., Muller, M., Pal, A., Masli, M., & Geyer, W. (2015). Inferring employee engagement from social media. In *Conference on Human Factors in Computing Systems - Proceedings* (Vol. 2015-April, pp. 3999–4008).	- Computer Science	- N/A	- Onboarding, culture fit, and engagement
39. Sharma, A., & Sharma, T. (2017). HR analytics and performance appraisal system: A conceptual framework for employee performance improvement. *Management Research Review*, 40(6), 684–697.	- Business, Management and Accounting	- HR analytics - Perceived accuracy - Performance appraisal - Performance improvement - Employee performance	- Performance assessment and development and employee lifetime values
40. Singer, L., Storey, M.-A., Filho, F. F., Zagalsky, A., & German, D. M. (2017). *People analytics in software development* (Vol. 10223 LNCS).	- Computer Science - Engineering	- People analytics - Developer analytics - Feedback - Social network analysis - Computer-supported collaborative work - Collaboration	- Collaboration

41. Sinha, V., Subramanian, K. S., Bhattacharya, S., & Chaudhuri, K. (2012). The contemporary framework on social media analytics as an emerging tool for behavior informatics, HR analytics and business process. *Management (Croatia)*, 17(2), 65–84.	- Business, Management and Accounting	- N/A	- Generic
42. Ulrich, D., & Dulebohn, J. H. (2015). Are we there yet? What's next for HR? *Human Resource Management Review*, 25(2), 188–204.	- Business, Management and Accounting - Psychology	- Outside inside approach - Strategy - Transformation - Future human resource management	- Generic
43. Varshney, K. R., Chenthamarakshan, V., Fancher, S. W., Wang, J., Fang, D., & Mojsilović, A. (2014). Predicting employee expertise for talent management in the enterprise. In *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 1729–1738).	- Computer Science	- N/A	- Workforce planning
44. Wang, J., Varshney, K. R., Mojsilovic, A., Fang, D., & Bauer, J. H. (2013). Expertise assessment with multi-cue semantic information. In *Proceedings of 2013 IEEE International Conference on Service Operations and Logistics, and Informatics, SOLI 2013* (pp. 534–539).	- Business, Management and Accounting - Computer Science	- N/A	- Workforce planning
45. Wawer, M., & Muryjas, P. (2017). The utilization of the HR analytics by the high and mid-level managers: Case from Eastern Poland. In *Communication, Management and Information Technology - Proceedings of the International Conference on Communication, Management and Information Technology, ICCMIT 2016* (pp. 97–106).	- Computer Science	- N/A	- Performance assessment and development and employee lifetime values
46. Wei, D. (2017). k-quantiles: L1 distance clustering under a sum constraint. *Pattern Recognition Letters*, 92, 49–55.	- Computer Science	- Workforce analytics - k-means++ - Proportional data - Compositional data - Centroid	- Generic
47. Wei, D., & Varshney, K. R. (2015). Robust binary hypothesis testing under contaminated likelihoods. In *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings* (Vol. 2015-August, pp. 3407–3411).	- Computer Science - Engineering	- Workforce analytics - Minimax - Signal detection theory - Label noise - Linear programming	- Generic
48. Wei, D., Varshney, K. R., & Wagman, M. (2015). Optigrow: People Analytics for Job Transfers. In *Proceedings - 2015 IEEE International Congress on Big Data, BigData Congress 2015* (pp. 535–542).	- Computer Science	- Workforce analytics - Enterprise transformation - Expertise analytics - Human capital management - Total variation distance	- Workforce planning
49. Weiss, C. (2016). Human resources strategy and change: Essentials of workforce planning and controlling. In *Handbook of Human Resources Management* (pp. 1343–1373).	- Business, Management and Accounting - Economics, Econometrics and Finance	- HR analytics - HR controlling - HR KPIs - HR planning - HR strategy - Job family - Job model - Resource planning - Scenarios - Simulation - Strategic capabilities - Strategic talent management - Strategic workforce planning - Critical jobs - Workforce analytics	- Workforce planning
50.		- Scheduling models	- Workforce planning

	Williams, J. C., Lambert, S., Pitt-Catsouphes, M., James, J., Sweet, S., Cahill, K., … Disselkamp, L. (2013). New Scheduling Models for the Workforce. In *Workforce Asset Management Book of Knowledge* (pp. 309–344).	- Business, Management and Accounting	- Work-life balance - Workforce asset management professional (WAM-Pro) - Workplace flexibility	
51.	Wroe, N. (2012). Innovations in talent analytics. *T and D*, 66(8), 30–31.	- Business, Management and Accounting	- N/A	- Generic
52.	Xu, H., Yu, Z., Yang, J., Xiong, H., & Zhu, H. (2016). Talent circle detection in job transition networks. In *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (Vol. 13–17-August-2016, pp. 655–664).	- Computer Science	- People analytics - Talent circle detection	- Sourcing
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1.	Angrave, D., Charlwood, A., Kirkpatrick, I., Lawrence, M., & Stuart, M. (2016). HR and analytics: why HR is set to fail the big data challenge. *Human Resource Management Journal*, 26(1), 1–11.	- Business, Management and Accounting	- HR analytics - Human resource information systems - Big data	- Generic
2.	Aral, S., Brynjolfsson, E., & Wu, L. (2012). Three-way complementarities: Performance Pay, human resource analytics, and information technology. *Management Science*, 58, 913–931.	- Business, Management and Accounting - Decision Sciences	- Human Resource Analytics - Incentive systems - Information technology - Performance pay - Production function - Principal-agent model - Complementarity - Enterprise systems - ERP - Productivity	- Performance assessment and development and employee lifetime values
3.	Bassi, L. (2011). Raging debates in HR Analytics. *People & Strategy*, 34, 14–18.	- Business, Management and Accounting	- N/A	- Generic
4.	Coco, C. T., Jamison, F., & Black, H. (2011). Connecting people investments and business outcomes at Lowe's: Using value linkage analytics to link employee engagement to business performance. *People & Strategy*, 34, 28–33.	- N/A	- N/A	- Onboarding, culture fit, and engagement
5.	DiBernardino, F. (2011). The missing link: Measuring and managing financial performance of the human capital investment. *People & Strategy*, 34, 44–49.	- N/A	- N/A	- Generic
6.	Douthitt, S., & Mondore, S. (2014). Creating a business-focused HR Function with Analytics and Integrated Talent Management, *People & Strategy*, 36(4), 16–21.	- N/A	- N/A	- Generic
7.	Falletta, S. (2014). In search of HR intelligence: Evidence-based HR Analytics practices in high performing companies. *People & Strategy*, 36, 28–37.	- N/A	- N/A	- Generic
8.	Giuffrida, M. (2014). Unleashing the power of talent analytics in federal government. *Public Manager*, 43, 7–10	- N/A	- N/A	- Generic
9.	Harris, J. G., Craig, E., & Light, D. A. (2011). Talent and analytics: New approaches, higher ROI. *Journal of Business Strategy*, 32, 4–13.	- Business, Management and Accounting	- Analytics - Talent management - Human resources - Decision making - Human resource management	- Generic
10.	Lawler III, E. E., Levenson, A., & Boudreau, J. W. (2004). HR metrics and analytics: Use and Impact. *Human Resource Planning*, 27, 27–35.	- N/A	- N/A	- Generic
11.		- N/A	- N/A	- Generic

	Levenson, A. (2011). Using targeted analytics to improve talent decisions. *People & Strategy*, 34, 34–43.			
12.	Mondare, S., Douthitt, S., & Carson, M. (2011). Maximizing the impact and effectiveness of HR Analytics to drive business outcomes. *People & Strategy*, 34, 20–27.	- N/A	- N/A	- Generic
13.	Pape, T. (2016). Prioritising data items for business analytics: Framework and application to human resources. *European Journal of Operational Research*, 252, 687–698.	- Decision Sciences - Mathematics	- Business analytics - Business intelligence - Data requirements - Human resources - Multi-criteria decision analysis	- Generic
14.	Rasmussen, T., & Ulrich, D. (2015). Learning from practice: how HR analytics avoids being a management fad. *Organizational Dynamics*, 44(3), 236–242.	- Business, Management and Accounting - Psychology - Social Sciences	- N/A	- Generic
	HCA Group List			
1.	Barrick, M. R., Thurgood, G. R., Smith, T. A., & Courtright, S. H. (2015). Collective Organizational Engagement: Linking Motivational Antecedents, Strategic Implementation, and Firm Performance. *Academy of Management Journal*, 58(1), 111–135.	- Business, Management and Accounting	- N/A	- Onboarding, culture fit, and engagement
2.	Bell, S. T., Villado, A. J., Lukasik, M. A., Belau, L., & Briggs, A. L. (2011). Getting Specific about Demographic Diversity Variable and Team Performance Relationships: A Meta-Analysis. *Journal of Management*, 37(3), 709–743.	- Business, Management and Accounting - Economics, Econometrics and Finance	- Teams diversity - Demographic diversity - Team diversity - Meta-analysis	- Diversity and inclusion
3.	Bowen, D. E., & Ostroff, C. (2004). Understanding HRM–Firm Performance Linkages: The Role of the “Strength” of the HRM System. *Academy of Management Review*, 29(2), 203–221.	- Business, Management and Accounting	- N/A	- Onboarding, culture fit, and engagement
4.	Call, M. L., Nyberg, A. J., Ployhart, R. E., & Weekley, J. (2015). The dynamic nature of collective turnover and unit performance: The impact of time, quality, and replacements. *Academy of Management Journal*, 58(4), 1208–1232.	- Business, Management and Accounting	- N/A	- Churn and retention
5.	Christian M. S., Garza A. S., & Slaughter J. E. (2011). Work engagement: a quantitative review and test of its relations with task and contextual performance. *Personnel psychology*, 64(1), 89–136.	- Business, Management and Accounting - Psychology	- N/A	- Onboarding, culture fit, and engagement
6.	Cole, M. S., Walter, F., Bedeian, A. G., & O’Boyle, E. H. (2012). Job Burnout and Employee Engagement: A Meta-Analytic Examination of Construct Proliferation. *Journal of Management*, 38(5), 1550–1581.	- Business, Management and Accounting - Economics, Econometrics and Finance	- Burnout - Construct redundancy - Construct proliferation - Construct validity - Engagement	- Onboarding, culture fit, and engagement - Wellness, health, and safety
7.	Costa P. L., Passos A. M., & Bakker, A. B. (2014). Team work engagement: A model of emergence. *Journal of Occupational and Organizational Psychology*, 87(2), 414–436.	- Business, Management and Accounting - Psychology	- Team work engagement - Team dynamics - Emergent states - Collective constructs	- Onboarding, culture fit, and engagement
8.	Crawford, E. R., LePine, J. A., & Rich, B. L. (2010). Linking job demands and resources to employee engagement and burnout: A theoretical extension and meta-analytic test. *Journal of Applied Psychology*, 95(5), 834–848.	- Psychology	- Employee engagement - Burnout - Job demands and resources - Challenge and hindrance stress - Meta-analysis	- Onboarding, culture fit, and engagement - Wellness, health, and safety
9.	Den Hartog, D. N., Boon, C., Verburg, R. M., & Croon, M. A. (2013). HRM, Communication, Satisfaction, and Perceived Performance: A Cross-Level Test. Journal of Management, 39(6), 1637–1665.	- Business, Management and Accounting	- Strategic HRM - Perceived HRM - Communication - Satisfaction - Unit performance	- Wellness, health, and safety - Performance assessment and development and employee lifetime values

	- Economics, Econometrics and Finance		
10. Dobrow Riza, S., Ganzach, Y., & Liu, Y. (2016). Time and Job Satisfaction: A Longitudinal Study of the Differential Roles of Age and Tenure. *Journal of Management*.	- Business, Management and Accounting - Economics, Econometrics and Finance	- Job satisfaction - Time - Age - Tenure - Pay - Longitudinal study	- Wellness, health, and safety
11. Fang, R., Landis, B., Zhang, Z., Anderson, M. H., Shaw, J. D., & Kilduff, M. (2015). Integrating Personality and Social Networks: A Meta-Analysis of Personality, Network Position, and Work Outcomes in Organizations. *Organization Science*, 26(4), 1243–1260.	- Business, Management and Accounting	- Social networks - Network position - Structural holes - Brokerage - Indegree centrality - Personality - Self-monitoring - Big Five personality traits - Meta-analysis	- Performance assessment and development and employee lifetime values
12. Harter, J. K., Schmidt, F. L., & Hayes, T. L. (2002). Business-unit-level relationship between employee satisfaction, employee engagement, and business outcomes: A meta-analysis. *Journal of Applied Psychology*, 87(2), 268–279.	- Psychology	- N/A	- Onboarding, culture fit, and engagement
13. Heavey, A. L., Holwerda, J. A., & Hausknecht, J. P. (2013). Causes and consequences of collective turnover: A meta-analytic review. *Journal of Applied Psychology*, 98(3), 412–453.	- Psychology	- Collective turnover - Organizational performance - Retention - Meta-analysis	- Churn and retention
14. Jiang, K., Lepak, D. P., Hu, J., & Baer, J. C. (2012). How Does Human Resource Management Influence Organizational Outcomes? A Meta-analytic Investigation of Mediating Mechanisms. *Academy of Management Journal*, 55(6), 1264–1294.	- Business, Management and Accounting	- N/A	- Churn and retention
15. Kehoe, R. R., & Wright, P. M. (2013). The Impact of High-Performance Human Resource Practices on Employees' Attitudes and Behaviors. *Journal of Management*, 39(2), 366–391.	- Business, Management and Accounting - Economics, Econometrics and Finance	- Strategic HRM - Commitment	- Onboarding, culture fit, and engagement - Churn and retention
16. Kunze, F., Boehm, S., & Bruch, H. (2013). Organizational Performance Consequences of Age Diversity: Inspecting the Role of Diversity-Friendly HR Policies and Top Managers' Negative Age Stereotypes. *Journal of Management Studies*, 50(3), 413–442.	- Business, Management and Accounting	- Age discrimination - Age diversity - Age stereotypes - Diversity-friendly HR-practices - Social identity theory - Structural equation modelling	- Diversity and inclusion
17. Leslie, L. M., Manchester, C. F., & Dahm, P. C. (2017). Why and When Does the Gender Gap Reverse? Diversity Goals and the Pay Premium for High Potential Women. *Academy of Management Journal*, 60(2), 402–432.	- Business, Management and Accounting	- N/A	- Performance assessment and development and employee lifetime values - Diversity and Inclusion
18. Locke, E. A., & Latham, G. P. (2002). Building a practically useful theory of goal setting and task motivation: A 35-year odyssey. *American Psychologist*, 57(9), 705–717.	- Medicine - Psychology	- N/A	- Performance assessment and development and employee lifetime values
19. Murphy, K. R. (2008). Explaining the Weak Relationship Between Job Performance and Ratings of Job Performance. *Industrial and Organizational Psychology*, 1(2).	- Psychology	- N/A	- Performance assessment and development and employee lifetime values
20. Nahrgang, J. D., Morgeson, F. P., & Hofmann, D. A. (2011). Safety at work: A meta-analytic investigation of the link between job demands, job resources, burnout, engagement, and safety outcomes. *Journal of Applied Psychology*, 96(1), 71–94.	- Psychology	- Workplace safety - Safety climate - Meta-analysis - Job demands - Job resources	- Onboarding, culture fit, and engagement - Wellness, health, and safety
21. Nishii, L. H. (2013). The Benefits of Climate for Inclusion for Gender-Diverse Groups. *Academy of Management Journal*, 56(6), 1754–1774.	- Business, Management and Accounting	- N/A	- Diversity and inclusion

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23. Park, T.Y., & Shaw, J. D. (2013). Turnover rates and organizational performance: a meta-analysis. *The Journal of Applied Psychology*, 98(2), 268—309.	- Psychology	- Meta-analysis - Organizational performance - Turnover rates	- Churn and retention
24. Rich, B. L., Lepine, J. A., & Crawford, E. R. (2010). Job Engagement: Antecedents and Effects on Job Performance. *Academy of Management Journal*, 53(3), 617–635.	- Business, Management and Accounting	- N/A	- Onboarding, culture fit, and engagement
25. Saks, A. M., & Gruman, J. A. (2014). What Do We Really Know About Employee Engagement? *Human Resource Development Quarterly*, 25(2), 155–182.	- Arts and Humanities - Business, Management and Accounting	- Employee engagement - Burnout - Job resources - Job demands - Personal resources	- Onboarding, culture fit, and engagement
26. Schaufeli, W.B., & Bakker, A. B. (2003). *Utrecht Work Engagement Scale*. Utrecht: Occupational Health Psychology Unit, Utrecht University.	- N/A	- N/A	- Onboarding, culture fit, and engagement
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Appendix D. Vendors' descriptions and the definitions they follow

Company	Description	Definition	Web Link
Deloitte	Smarter insights with workforce data analytics. Analytics perspectives and solutions Can you predict which high performers are at risk of leaving months before they resign? Merge external data with your own business metrics to project next year's workforce demand? And can you triage resumes to predict employee success and tenure – before you hire? Here are just a few examples of how companies can gain smarter insights and stronger outcomes with workforce data analytics and cognitive computing.	Not specified	https://www2.deloitte.com/us/en/pages/deloitte-analytics/solutions/analytics-in-action-workforce.html
TechTarget	We are a trusted information hub for all the essential human resources (HR) technology you rely on to do your job. We know that HR leaders have many difficult, strategic technology decisions to make when trying to find the best employees, keep them happy, and get them paid.	*Workforce analytics* is a combination of software and methodology that applies statistical models to worker-related data, allowing enterprise leaders to optimize human resource management (HRM).	http://searchhrsoftware.techtarget.com/about http://searchhrsoftware.techtarget.com/definition/workforce-analytics

Competitive Analytics	Competitive Analytics [CA] helps organizations integrate all the necessary analytics and develop a strategy to truly get the best from your team. We help you understand who your top performers are, where inefficiencies may occur, and how you can recruit, empower, and motivate other employees. CA helps you ensure that the data being used is timely, clean, and accurate. Because organizations often have employee related data spread throughout departments, in myriad file formats, and within multiple systems, Competitive Analytics blends data sources to develop a complete workforce database, which can then be easily used to develop your employee analytics. Competitive Analytics displays our comprehensive labor analyses in easy-to-interpret, interactive dashboards so executives can make employee related decisions immediately.	Gartner defines *Employee Analytics*, also known as Workforce Analytics, as, advanced set of data analysis tools and metrics for comprehensive workforce performance measurement and improvement. It analyzes recruitment, staffing, training and development, personnel, and compensation and benefits, as well as standard ratios that consist of time to fill, cost per hire, accession rate, retention rate, add rate, replacement rate, time to start and offer acceptance rate.	http://competitiveanalytics.com/employee-analytics/
McKinsey & Company	Identify and enable talent-driven performance Top employees outperform average employees by up to eight times. To stay ahead, leading companies identify, attract, develop, and retain these top employees. How do they do it? By developing a people strategy that is based on data and analytics.	*People Analytics*-the application of advanced analytics and large data sets to talent management	https://www.mckinsey.com/business-functions/organization/how-we-help-clients/people-analytics https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/using-people-analytics-to-drive-business-performance-a-case-study
Accenture	Imagine all the questions you've ever had about your workforce answered: which people are needed for specific projects? Do you have the resources you need to successfully grow your organization? How are individuals performing against KPIs? Analytics reveals the answers, giving you solid, reliable insights so you can plan, recruit and manage with confidence. We'll help you analyze HR trends, set workforce capacity and capability goals, track progress, monitor performance and automate services. By equipping you with integrated, strategic insights we can help you speed up decisions, reduce risk and empower your management team.	*Human Capital Analytics* help lead to better focus, employee experience and ROI	https://www.accenture.com/us-en/service-accenture-analytics-talent-and-hr-analytics https://www.accenture.com/nz-en/service-fei-digital-hr-transformation-inform-analytics
IBM	HR analytics enable organizations to use their wealth of employee data to make better decisions about their workforces and improve operational performance. From attracting top talent, to accurately forecasting future staffing needs or improving employee satisfaction, HR analytics tools empower organizations to align HR metrics with strategic business goals.	*HR Analytics*-a data-driven approach to building a smarter workforce	https://www-01.ibm.com/software/analytics/solutions/operational-analytics/hr-analytics/
PWC	Our tactical and predictive analytics programs will help you address specific workforce trouble spots so you can manage issues before they appear. We'll show you how to build your Talent Analytics solutions. Point solutions demonstrate ROI of people analytics to the business	Not specified	https://www.pwc.com/us/en/hr-management/people-analytics/predictive-analytics.html

	We have a wide range of experience assisting clients with targeted analytic, modeling, and forecasting requirements to address the top workforce concerns today. We have pre-built talent analytics services to cover the full HR/employee lifecycle – from talent acquisition to performance, safety & learning management, to retention and retirement – all designed to assist your organization solve critical workforce and business objectives. We offer analytics around total rewards that will enable your organization to optimize across different benefits and compensation options. Every talent analytics and predictive service we offer has one goal in common: apply advanced analytic techniques to solve a critical workforce problem and thereby, demonstrate value of talent analytics to the entire organization.		
Kronos	Transform your workforce data into actionable insights. Organizations need to identify, predict, and manage opportunities for cost savings and productivity gains — all while improving the quality of their products and services. But how can they achieve productivity gains and stay within budget when they lack a reliable way to measure and analyze workforce performance?	Not specified	https://www.kronos.com/products/workforce-central-suite/workforce-analytics
SAP SuccessFactors	Improve business decisions with trusted intelligence from SAP SuccessFactors Workforce Analytics. Benefit from the technology and expertise of a global leader in people analytics and business intelligence solutions to accelerate your organization's understanding of Big Data in HR and use workforce data strategically to drive business impact. SAP makes workforce analytics simple and accessible for HR professionals, analysts, and business partners so they can quickly and accurately answer key questions about your workforce and influence talent and business decisions being considered by your managers and executives.	Not specified	https://www.successfactors.com/en_us/solutions/workforce-planning-and-analytics/workforce-analytics.html
Talent Analytics	Why Talent Analytics? 8 Compelling Reasons to Engage with Us: 1. Self Funding Projects – Our Projects Pay for Themselves; 2. High Volume, High Turnover Roles; 3. Predictions are both Pre-Hire and Post-Hire; 4. Business Results (not HR Results); 5. No Distractions; 6. Globally Recognized Leaders; 7. Cloud Deployment Platform, Advisor; 8. Machine Learning – Models Continuously Recalculate, Learn and Update	Not specified	http://www.talentanalytics.com/why-talent-analytics/
Ultimate software	HR leaders use workforce analytics in various forms, such as predictive and prescriptive analytics. Predictive Workforce Analytics helps managers comb through mounds data to determine which employees have the	*Workforce analytics* describes a set of tools that measure, characterize and organize sophisticated employee data. These tools are used to present detailed employee performance to provide a better	https://www.ultimatesoftware.com/what-are-workforce-analytics

	greatest potential of success with the organization. The data also predicts which employees are most likely to leave in the near future. Prescriptive Workforce Analytics prescribes actions HR leaders can take to help develop and retain key members of the workforce, based on data uncovered from predictive analytics. Both are an essential part of workforce analytics and when used together, these tools can make all the difference! Why Do Companies Invest in Workforce Analytics? All great companies are made up of the right people in the right positions. Workforce analytics allows HR leaders to determine who the right people are, which tasks suit them best and how to ensure they remain satisfied in their roles. Ultimate Software has designed workforce analytics tools that are easy to understand and utilize effectively. Analytics aren't just for statisticians anymore. A growing number of organizations are using analytics to examine and act upon data about their people in the workplace. Known as workforce analytics, these sophisticated tech tools are changing the HR game, and those companies willing and able to harness the power of Big Data for analytics are seeing great gains and meaningful advantages over their competition. UltiPro® At Ultimate Software, our award-winning solution for HR, payroll, and talent management, UltiPro®, offers a range of predictive and prescriptive analytics designed to combine managers' expertise with proven algorithms. The winning result? Knowledge without bias.	understanding and assist in overall management.	
Visier	Visier Workforce Intelligence is a cloud-based people strategy platform that provides answers to hundreds of pre-built, best practice questions, across a range of HR and business topics. Unlike the reports offered by your HR management systems, Visier delivers insights. Insights that reduce resignations. Sharpen recruiting effectiveness. Optimize learning. And drive business outcomes.	Not specified	https://www.visier.com/solutions/
QuestionPRO	Employee analytics tool providing 360 reviews, online surveys, weekly pulse to increase employee retention, improve morale, and create workforce efficiency.	Not specified	https://www.questionpro.com/workforce/
TalentLMS	Simple and comprehensible analytics about everything that happens inside your elearning environment.	Not specified	https://www.talentlms.com/
Cornerstone	What Are the Benefits of People Analytics? People analytics helps organizations to make smarter, more strategic and more informed talent decisions. With people analytic, organizations can find better	*People analytics*, also known as talent analytics or HR analytics, refers to the method of analytics that can help managers and executives make decisions about their employees or workforce. People analytics applies statistics,	https://www.cornerstoneondemand.com/glossary/people-analytics

applicants, make smarter hiring decisions, and increase employee performance and retention. Cornerstone's suite of people analytics products apply sophisticated data science and machine learning to help organizations more efficiently and effectively manage their people. Cornerstone's analytics suite give organizations options for viewing, understanding and acting on talent data across the entire employee lifecycle. This includes Cornerstone View, an interactive data visualization application that gives business leaders deeper intelligence about their people, Cornerstone Planning, an intuitive workforce planning application that helps organizations easily create, manage and execute accurate hiring plans over multiple time horizons, as well as Cornerstone Insights, its predictive and prescriptive analytics solution that equips business leaders with the intelligence to better recruit, train, manage and develop their people.	technology and expertise to large sets of talent data, which results in making better management and business decisions for an organization. People analytics is a new domain for most HR departments. Companies are looking to better drive the return on their investments in people. The old approaches of gut feel is no longer sufficient.

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