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Bachelor Thesis

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Title:

Re-tooling Human Resource Management. A critical analysis of chances, risks and barriers of People Analytics in Human Resource Management

Date of submission:

09/03/2018

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Abstract

Growing availability of data and exploitation of new data sources have transformed not only private life but also increasingly shape business functions. In the light of rising global competitive pressure, Human Resource Management has now begun to embrace the potential of utilizing data in form of People Analytics to overcome strategic deficits. Based on an extensive literature review the purpose of this thesis is to critically analyze postulated chances of People Analytics for Human Resource Management as well as outlining possible risks and potential implementation barriers. Findings indicate that despite clear chances for Human Resource Management, severe barriers are causing a current infancy stage of People Analytics in companies. Main implementation barriers identified are a lack of data quality, access and analytical skills, privacy issues, implementation costs, a lack of leadership commitment and cultural change readiness. To what extent the People Analytics hype will develop into management reality and lead the strategic transformation of HRM will therefore depend on whether companies are able to counter outlined barriers with effective strategies.

Keywords: Analytics, Big Data, Decision Making, Human Resource Management, People Analytics, Predictive Analytics, Strategic Human Resource Management

JEL classification: J20, J71, M12, M5, 015

“Blind faith has no place in professional practice.”

(Rousseau et al., 2011, p. 221)

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LIST OF ABBREVIATIONS

HR:	Human Resources
HRM:	Human Resource Management
KPI:	Key Performance Indicator
ROI:	Return on Investment
SHRM:	Strategic Human Resource Management

1 Introduction

1.1 Research problem

Companies are obliged to make decisions every day in order to survive in the increasingly competitive business environment and the same applies to their respective human resource (HR) managers in charge. Decisions of not only who to hire but also where to look for applicable candidates and how to design the selection procedures, how to effectively train and motivate employees and which steps to take in order to increase employee retention and decrease personnel fluctuation are all strategically pivotal decisions.

But with the lack of objective tools to analyze success factors and weaknesses, personnel decisions in organizations are to a large degree based on personal assessments and subjective opinions (cf. Bodie et al., 2016, p. 964). This does not only lead to distorted decision-making processes that are influenced by unconscious biases and stereotypes (cf. Rhode, 2017, p. 316) but in the long run harms the company's competitiveness.

Without a data-based connection between investments in HR programs and organizational outcomes the needed strategic cooperation between HR managers in their role as strategic partners and top level management is prevented (cf. Soundararajan et al., 2017, p. 2). Considering the fact that 50 to 75 percent of total costs of an organization relate to costs of payroll and other HR programs, the extent of the problem becomes visible (ibid., p. 14).

Following the principle of "If you can't measure it, you can't manage it" (Kaplan et al., 1996, p. 21) companies now increasingly make use of data analysis in various business areas i.e. to predict business trends, to manage risks or to identify the best marketing strategies. But until now companies have not made use of sophisticated data analysis in the area of HR (cf. Boudreau et al., 2017, p. 119). The introduction of the concept of People Analytics (also 'workforce analytics', 'HR analytics', 'talent analytics' or else) to Human Resource Management (HRM) processes is now expected to change this.

People Analytics is using various statistical methods in order to analyze current and historical intra-company as well as external data. By detecting patterns and correlations it is said to be enabled to make assumptions about the future (cf. van den Heuvel & Bondarouk, 2017, p. 160). One of the promises of People Analytics therefore is to be able to make evidence-based decisions considering all aspects of HRM and thus to increase the objectivity and reliability of decisions (cf. Andersen, 2017, p. 136).

By critically analyzing the chances, risks and barriers of implementing People Analytics in HRM the aim of this bachelor thesis is to show the potentials of People Analytics as a game changer for HRM. The obtained findings will reveal to what extent an implementation of People Analytics will be advisable for companies given the current state of research.

1.2 Course of investigation

After introducing the topic, a critical analysis of the current state of HRM will be given. By pointing out current trends and influencing factors shaping the future of HRM and uncovering deficits of traditional HRM, the necessity of a new evidence-based approach as postulated within the idea of People Analytics becomes obvious.

The next chapter will focus on the concept of People Analytics. The aim of this chapter is to explain what People Analytics is, how it works, and what possible areas of application in HRM are by examining both theoretical and real life examples. This then forms the basis which allows a subsequent analysis of chances and risks of People Analytics. Furthermore, the current implementation rate of People Analytics will be examined. These findings will later support the analysis of implementation barriers and strategies.

Combining the two previous topics, the aim of the fourth chapter is to critically analyze possible chances of applying People Analytics to HRM in the light of previously highlighted current deficits of HRM as well as dealing with risks and implementation barriers. Implementation strategies giving guidance on how to approach the implementation of People Analytics in HRM will build on outlined implementation barriers. Weighing both benefits and risks, a final assessment of the impact of People Analytics in HRM, given the current research, will be conducted.

Finally, an outlook of the expected development of People Analytics in the future will be given.

Given the fact that People Analytics is a relatively new discipline which to this date lacks a broad range of empirical research, this thesis is mainly focusing on a number of authors leading the field with their research and expertise.

2 Human Resource Management: A critical analysis of the current status

2.1 Conceptual framework, tasks and objectives

In order to assess possible implementation areas of People Analytics in HRM, the following chapter focuses on the tasks, objectives and functions that HRM currently fulfills in companies, its corresponding economic value and strategic importance to lay the theoretical foundations of this thesis.

The famous Hawthorne experiments, a series of studies conducted by Elton Mayo and F. J. Roethlisberger between 1924 and 1933, revealed for the first time that employee productivity is not only influenced by monetary incentives but also by societal and psychological factors (cf. Roethlisberger et al., 1941). Since then, companies have tried to capitalize these findings by developing adequate management philosophies and work structures (cf. Carrell et al., 2000, p. 6). They realized that human resources, which according to Boxall et al. (2007, p. 1) include the "[...] the knowledge, skills, networks and energies of people and, underpinning them, their physical and emotional health, intellectual capabilities, personalities and motivations [...]", require a far more complex management approach than capital or land resources. Consequently, the former 'Personnel Management' with a mainly administrative focus in the past shifted to todays 'Human Resource Management' which views human resources as a critical strategic success factor (cf. Wright et al., 2001, p. 701).

HRM can therefore be understood as the "[...] policies, practices and systems that influence employees' behavior, attitudes, and performance [...]" (Noe et al., 2016, p. 3). Simply put, HRM focuses on employing the right number of people with the right skills, experience and competencies in the right jobs at the right time at the right cost. Besides these organizational objectives, HRM is also pursuing societal objectives as well as employee objectives. In order to be socially responsible, HRM is obliged to contribute to meeting the needs and challenges of society by i.e. complying with legal and ethical standards, respecting human rights and the environment. At the same time, HRM is responsible for helping employees achieve their individual career goals (ibid., p. 7-14).

Achieving these goals, HRM traditionally operates on a variety of different dimensions as shown in Figure 1.

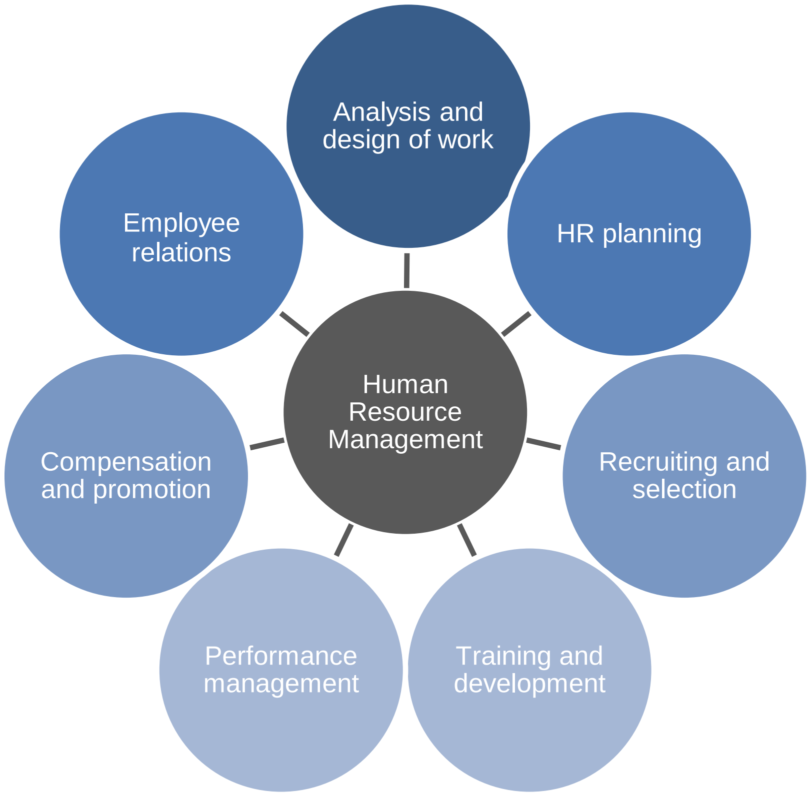

Figure 1: Dimensions of HRM

Source: based on Noe et al., 2016, p. 3

The starting point of every HR measure is the analysis of staffing requirements of the company in terms of needed skills and know-how as well as in quantitative terms. At the same time, HRM is in charge of structuring work and jobs in a way that allows employees to use their skills and abilities in the most productive way (cf. Huselid, 2007, pp. 45-46). HR planning then captures this analysis by deriving adequate strategies to meet the company's personnel needs. Both recruiting and selection as well as training and development have a huge influence on the available skills and know-how of human resources. The aim is to close an identified talent gap by hiring highly qualified employees and offering those adequate training possibilities to continuously build up or adjust their skills as needed to meet the company's goals. Performance management procedures are dealing with the recording of performance, behavior and potential of employees which is often tied to promotion and compensation structures. Another important function of HR is the management of communication and relationships amongst employees in a company to create a productive work environment and increase employee satisfaction (cf. Noe et al., 2016, p. 3).

The link between HRM practices and organizational performance has been subject to ongoing scientific research (cf. Koch et al., 1996; Becker et al., 1998; Guest et al., 2011). The development of the resource-based view in 1991 (cf. Barney, 1991, p. 105 ff.) which implicates that companies can gain sustainable competitive advantage on the basis of internal resources, caused companies to shift their outward focus inwards. Barney states that a resource needs to meet four criteria, i.e. it needs to be valuable, rare, inimitable and organized, to be the source of competitive advantage. In his opinion, human resources are both rare as well as difficult to imitate and as such, if organized effectively, bear huge potential of being a critical source of competitive advantage (cf. ibid.).

Although the resource-based view has also faced criticism (e.g. for being tautological as well as for neglecting the business environment of a company (cf. Priem et al., 2001) it laid the basis for a changing perspective of human resources and their management. The prevailing belief that employees predominantly represent cost factors that need to be minimized was revoked. As scientific studies were able to prove the impact of HR practices on the performance of the firm (cf. Wright et al., 2004), HRM now faces the challenge of designing adequate policies and structures that allow the company to utilize these capabilities.

With the development of Strategic Human Resource Management (SHRM), which encompasses the activities performed by the HR function supporting the achievement of a company's long term strategic goals (cf. Allen et al., 2007, pp. 88-90), HRM has been forced to transform its function from an “[...] administration role to personnel to business partner and now to key player at the strategic level [...]” (Soundararajan et al., 2017, p. 15) to support business needs. The growing importance of HR taking on a strategic role and collaborating with top management is also reflected in various statements by business leaders highlighting the strategical value of human resources and hence, the significance of their HR leaders to strategic success (cf. Boudreau et al., 2017b, p.120).

"Businesses grow or die based on the quality of their people,

so the human resource executive role is arguably the most strategic in the company.

If I weren't the CEO now, I'd probably want to be the CHRO."

- Owen Mahoney, CEO of Nexon (Boudreau et al., 2017a)

Pursuing its new strategic role and contributing a noticeable and verifiable proof to value creation, HRM needs to demonstrate its value to the company. In this context it is influenced by a number of trends deriving from the dynamic environment it operates in which will be examined next.

2.2 Current global trends shaping Human Resource Management

The business environment of organizations has always been subject to transformation, causing all management functions including HRM to adapt.

2.2.1 Changes in the work force

Globalization through advances in communication, transportation and infrastructure has caused the "war for talents", as declared by McKinsey & Company in 1997 (cf. Michaels et al., 2001, p. 1), to intensify. An aging workforce together with a decline in birth rates and an increasing life expectancy shifts the age distribution of the workforce. For example examining the situation in the United States, the Bureau of Labor Statistics projects that the share of people aged 55 and older will grow from 22.4 percent in 2016 to approximately 24.8 percent in 2026 as shown in Figure 2 and as a result the labor force participation rate is expected to decrease from 62.8 percent in 2016 to 61.0 percent in 2026 (cf. Bureau of Labor Statistics, 2017, p. 2). At the same time, HRM has to be able to understand and manage the needs from three or four generations simultaneously.

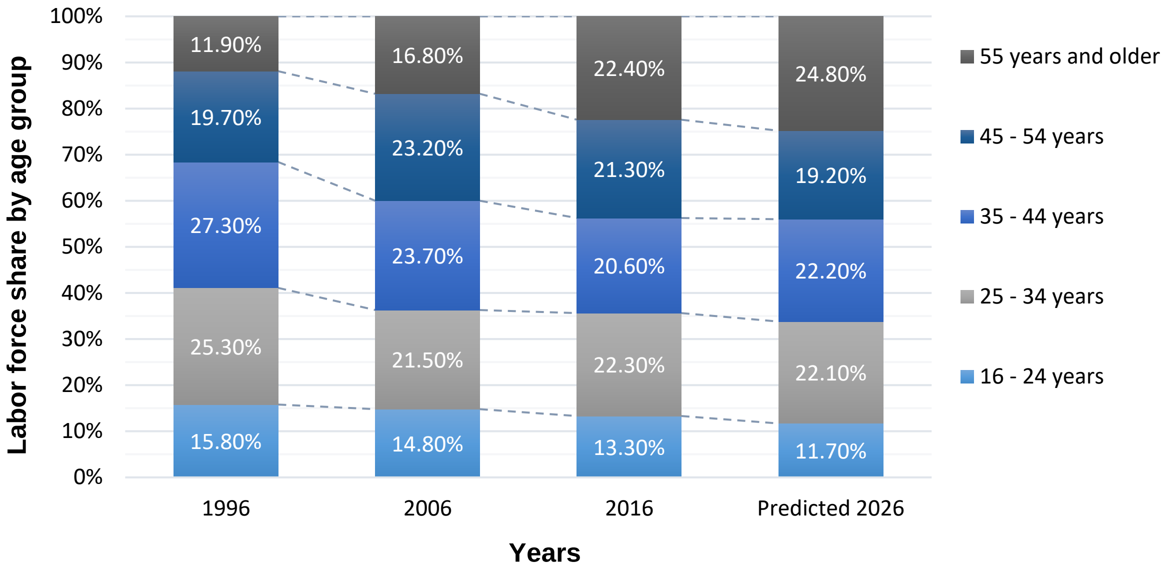

Figure 2: U.S. Labor force share by age group, Years 1996 - 2026 (predicted)

Source: U. S. Bureau of Labor Statistics, 2017, p.2

But the work force is not only getting more diverse in terms of age, it also becomes more diverse in ethnical, racial and gender terms (cf. Dessler, 2017, p. 43). As geographic borders as well as regulatory hurdles are diminishing, the mobility of workers is growing, resulting in employees nowadays possessing diverse cultural backgrounds which requires additional managerial effort. Additionally, while women over the decades have increasingly participated in the labor force, e.g. in 2017 45.8 percent of total labor force in the United States were female compared to 44.3 percent in 1990 (Worldbank, 2018), they are still underrepresented in top management positions (cf. Goryunova et al., 2017, p. 13). As a result, the concept of diversity management and resulting advantages for the workplace gained more and more importance. In this light HRM needs to ensure that all policies are free of stereotypes and biases and manage the new diversity in a way that contributes to organizational performance.

2.2.2 Changes in the nature of work

Not only workforce characteristics are changing, but also the nature of work itself. During the recent years there has been a noticeable shift away from traditional office work carried out on-site to an increasing dissemination of flexible work arrangements, e.g. in the form of remote work or telecommuting, flexible work hours and agile work. (cf. Pease et al., 2014, p. 5).This is a result of on the one hand changing employee’s needs and especially the desire to achieve a better work-life balance, and on the other hand the response to the global talent war. In general, research has also highlighted the influence of the Millennials, i.e. the generation born between 1980 until 2000, as they are more and more entering the workforce playing a major role in the current and future design of work as well as workplaces (cf. Isson et al., 2016, p. 37). While generalizations about a large group of individuals should be treated with caution, Millennials tend to put a greater value on an open feedback culture inside the organization thus initiating a shift of power in the employee-management relationship. Furthermore, it has been stated that Millennials tend to seek for meaningful work which goes beyond the technical execution of tasks (cf. Peae et al.., 2014, p. 3).

Independent from the influence of Millennials entering the workforce is a trend that relates to decreasing employee loyalty and job tenure (cf. Isson et al., 2016, p. 35). In their latest economics news release from September 2016, the U. S. Bureau of Labor Statistics stated that the median number of years that a worker stays with one company decreased from 4.6 years in January 2014 down to 4.1 years in January 2016 in the United States. A difference between median employee tenure of older workers compared to younger workers also revealed that younger workers tend to change employers more frequently (cf. Bureau of Labor Statistics, 2016).

Furthermore the nature of work is shaped by the knowledge-based structural change as well as the growing importance of the service sector along with an increasing share of employees with academic qualifications. This means that companies nowadays are faced with a more complex workforce in regards to educational backgrounds (cf. Dessler, 2017, p. 45).

In order to be able to attract and retain future talent, it is necessary that HRM understands the changing needs of the workforce, i.e. what attracts, motivates and retains employees and based on this knowledge, make the needed changes in the nature of work and position the company as a desirable workplace for all generations (cf. Pease et al., 2014, p. 5).

2.2.3 Changes in technology

Rapid changes in technology and, along with it, the advancing progress of digitalization in business is another current trend influencing HRM. New technological tools and information technology have changed almost every HRM practice, i.e. from using online job boards and social media for recruiting, sophisticated e-learning platforms for training and e-performance systems to digital personnel files, compensation systems and employee self-service systems (cf. Jain, 2014, pp. 7-12). As a consequence, former administrative HR functions should theoretically become more and more substituted by technology solutions which would enable HR to spend more time on strategic tasks and collecting and transforming data into valuable business insights. Therefore, companies need to carefully examine and invest in these tools in order to stay competitive as well as to build up the competencies and skills in HR needed to efficiently operate these tools. The increasing use of new media by companies, such as social networks or social hiring channels, to support recruitment has led to the emergence of digital talent data and metrics. HR needs to focus on analyzing this data to optimize recruiting efforts in order to stay ahead of competition in the war for best talent (cf. Isson et al., 2016, p. 34).

It should be noted that the trends outlined here are also influencing each other mutually, e.g. the advances in technology are enabling the shift in the design of work, thus increasing overall complexity issues. Furthermore, the list of influencing factors mentioned here should not be seen as a complete list but more as an approach to understand the current changes in the business environment. To sum up, in order to adapt to these rapid and complex changes companies need to be able to predict and manage their different talent needs. This can only be achieved by strategic support from HRM and indicates that “Business and HR leaders can no longer continue to operate according to old paradigms [...]” and “They must now embrace new ways of thinking about their companies, their talent, and their role in global social issues [...]” (Deloitte, 2017, p. 3).

2.3 Deficits of today's Human Resource Management

As outlined in the previous chapter, HRM needs to react to a number of trends and is more than ever under great pressure to serve as a strategic business partner. The following chapter will therefore examine how far today's HR function is currently able to react to those challenges.

In 1981, i.e. almost forty years ago, an article called "Big Hat, No Cattle: managing Human Resources" by W. Skinner published in the Harvard Business Review declared that the HR function at that time failed to deliver a real contribution to business success. Skinner stated that although HR leaders dressed and looked like the other business leaders back then, their outer appearance had little to do with their actual input. (cf. Skinner, 1981, p. 106). Twenty-five years later, Keith H. Hammonds, chief deputy editor of Fast Company, a leading economic journal, again stirred the heated discussion about the role of HRM. In his widely discussed article "Why We Hate HR" (2005) he concludes that HR professionals although pursuing to become a strategic partner and gaining a seat at the table with other business leaders, are wasting their potential performing administrative, routine tasks with no business value and as such "HR people are, for most practical purposes, neither strategic nor leaders [...]" (Hammonds, 2005, p. 40).

Although there seems to be consensus in the way that the HR function underwent major changes and improvements investing heavily in more sophisticated tools which lead to greater efficiency in traditional HR tasks mainly related to administrative functions, HR professionals currently do not perform the strategic role as suggested by academic research (cf. Boudreau et al., 2007, pp. 8). Conducting a long term study from 1995 until 2013 measuring how the HR function is responding to changes in the workforce, technology and global competition by redesigning HR functions, policies and practices by surveying 417 HR professionals worldwide, Lawler III and Boudreau even find that there has been no to only little change of how HR professionals spend their time. Thus they conclude that there seems to be a surprising gap between the change that has happened in the business world since 1995 and the way that HR hasn’t been able to respond to that change in becoming a strategic contributor (cf. Lawler et al., 2015, pp. 16 - 21). Furthermore a study performed by Deloitte in their annual "Global Human Capital Trends 2015" based on data from surveys and interviews taken by 3,300 HR and business leaders in 106 countries, concerning the question whether HR organizations currently possess the needed skills to meet business needs, revealed a current "capability gap" (Deloitte, 2015, p. 62). Only five percent of the respondents rated the performance of their HR organization as "excellent", while 31 percent perceived the performance as "good", 32 percent as "adequate", 22 percent as "getting by" and 10 percent as "underperforming" (Deloitte, 2015, p. 62). As a conclusion, “HR is not keeping up with the pace of change in business [...]” (ibid.).

Why is HRM currently unable to get a “seat at the table” along with the other strategic functions such as finance, marketing and sales? Soundararajan et al. (2017, p. 1) as well as Boudreau et al. (2004, p. 27) see the reason for this in the inability of HRM to link investments made in HR programs to organizational success. This phenomenon is also referred to as the black box of HR investments (Gardner et al., 2001, p. 5). Although a number of contributions provided evidence that HRM activities generally have a positive impact on organizational effectiveness in the past, little is known about how each individual decision made in HRM actually relates to gained competitive advantage and drives strategic success. Besides this lack of cause and effect, HRM also differentiates from other business functions in the way that HR decisions are currently predominantly being made as “[...] HR lacks the type of analytical and data-based decision making capability that are needed to influence business strategy” (Lawler III et al., 2004, p. 28).

For a long time, the theory of the “homo economicus” (based on Mill, 1836, p. 321) i.e. the belief that humans will always make rational decisions to maximize economic utility, was widely accepted. But later research provided evidence that falsified this theory. Pioneers in the field of behavioral economics like Kahneman and Tversky find that people are impacted by the way information is presented to them. Furthermore, Kahneman divides the human brain into two systems whereas the first system acts intuitive and unconsciously and the second system acts using cognitive resources and thus requires more thinking capacity and energy. He concludes that in order to make more efficient decisions and save valuable resources, people tend to use the first system more often (cf. Kahneman, 2011, pp. 19 - 21).

HR managers need to make dozens of decisions every day along all HR dimensions – from recruiting the best candidate, to how to design effective trainings and whom to promote. As previously examined, the business environment changes at rapid speed urging companies to react just as quickly. While other business functions have tackled this development with evidence-based decisions based on data analyses (cf. Fitz-enz et al., 2014, p. xvi), many HR decisions are in fact based to a large degree on personal experience, intuition or heuristics (cf. Davenport et al., 2010, p.1). An example for this in recruiting is the widespread use of unstructured interviews instead of structured interviews and aptitude tests (cf. Dana et al., 2013, p. 512, cf. Schuler et al., 2007, p. 61) although they are scientifically proven to be better in predicting future job performance (cf. Highhouse, 2008, p. 336).

While subjective decision making without objective measures might increase efficiency in decision making processes, it bears the potential risk of being vulnerable to wrong conclusions (cf. Fischer et al., 2005, pp. 364 - 368). Again, a relevant example in this area are wrong decisions in the recruiting process. It should be noted that wrong decisions of course also appear within other HR dimensions, but the measurable impacts of wrong decisions in recruiting makes it a vivid example. A study conducted in 2015 by PAPE Lab, a personnel consulting company, questioned 3,000 HR managers from small, medium and large enterprises concerning their current recruiting processes and recruiting trends in 2016/2017. It revealed that almost a third of respondents, i.e. 29 percent, stated that they made wrong staffing choices and mentioned as one of the main reasons for this time pressure to fill vacant posts (cf. PAPE Lab, 2016). The negative impacts of wrong staffing choices include increased hiring costs, loss of revenue due to lower productivity and lower work ethics of remaining workers and business disruptions due to higher employee turnover. [1]

Another negative aspect of basing decisions on own experiences and personal assessments is that it creates space for bias, often unconscious, and stereotypical thinking related to race, gender, sexual preference or religion in HRM. Examples include confirmation bias (p. 81), anchoring bias (p. 127), representativeness heuristics (p. 151) as well as the halo effect (p. 4) (cf. Kahneman, 2011). While biases as unconscious mechanisms of the brain can be helpful to reduce information complexity in everyday day life decision making, they can have negative implications in the business context due to potential distorted perceptions of reality. Biases potentially impact HR decisions in recruiting and selection, performance appraisal and compensation and may especially lead to unintentional discrimination against certain age groups (such as older workers), minorities and women. A prominent example for

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[1] It should be noted that employee turnover is not always negative as it can also lead to higher productivity if low performing employees are substituted with high performing employees, i.e. functional turnover. What is meant here, however, is dysfunctional turnover, i.e. high performing employees who drive organizational performance leaving the company (cf. Boudreau & Berger, 1985)

this are fixed role expectations of men and women having a negative impact on woman's career progression[2] (cf. Bowles et al., 2007, p. 85; cf. Heilmann, 2001, p. 657). The power of stereotypes and biases have been demonstrated in numerous experiments; a very illustrative one is the "Heidi/Howard case study", a business case conducted with business students at Harvard Business School and many other occasions. While half of the students were presented with the biography of Heidi Roizen who was a successful Silicon Valley venture capitalist, the other half was presented with exactly the same biography except that the name was changed to Howard Roizen instead. When asked to rate Heidi or Howard respectively in terms of perceived competency and likeability, the majority of students, though rating Heidi and Howard equally competent, perceived Howard to be more likeable and furthermore would rather work with him (cf. Bohnet, 2016, p. 29). All in all, persisting biases are counterproductive to create a more diverse, inclusive workplace needed to compete in the increasingly competitive, changing globalized business environment as outlined in the previous chapter.

Different authors (cf. Lawler III et al., 2004, p. 34; cf. Davenport, 2010, pp. 2-3 ; cf. Fitz-enz et al., 2014, pp. 5-6) have emphasized the more sophisticated, systematic use of data in HR decision making in form of People Analytics to be the right approach to HRM's current deficits and needed tool in order to make valuable, measurable contributions and thus transforming into a strategic partner to top-level-management. In order to understand this new approach the next chapter will examine the current use of data in HRM and in how far it lacks strategic insight.

2.4 Working with data in Human Resource Management

The nature of HRM itself creates a great amount of data. While the collection of employee data has always been part of HR practices, the way this data it is stored, managed and used has changed over time. (cf. Boudreau, 2007, p. 189). In 1978, Fitz-enz was the first one to formulate the idea of measuring HR activities and their influence on organizational performance in his article "The Measurement Imperative" (cf. Fitz-enz, 1978). Since then companies have increasingly started to collect data

[2] Biases and stereotypes of course also affect men, e.g. when applying for traditionally female-dominated occupations.

from all HR dimensions such as employee turnover, recruitment, compensation and training and developed different measurement approaches ranging from ad hoc measures and key performance indicators (KPIs), benchmarks to data systems and scorecards.

While these measures undoubtedly increased efficiency in HR practices, as already mentioned in the previous chapter, a clear impact on effectiveness on same practices is missing. Cascio et al. sum up this experience of using data in HRM in their image of a wall that HRM seems to hit, as shown in Figure 3 (Cascio et al., 2011, p. 9

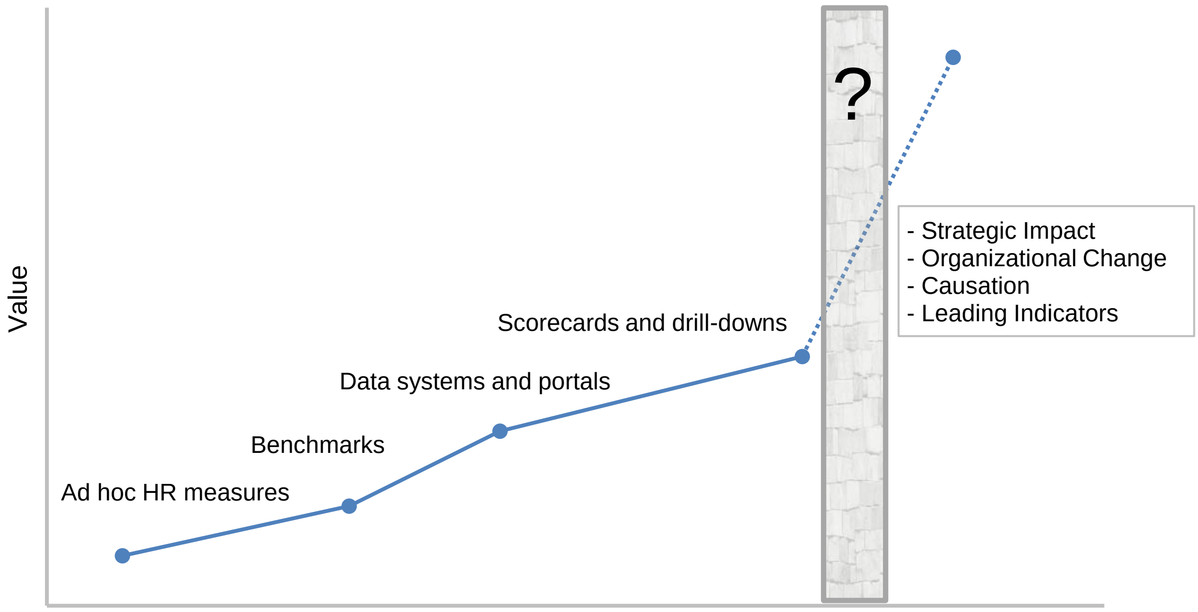


Figure 3: The wall in HR measurement

Source: Cascio et al., 2011, p. 9

They conclude that although “There is increasing sophistication in technology, data availability, and the capacity to report and disseminate HR information, […] investments in HR data systems, scorecards and ERP fail to create strategic insights needed to drive organizational effectiveness” (ibid., p. 8). In their book “Beyond HR. The new science of Human Capital” Boudreau and Ramstad (2007, p. 38) see the reason for this in the mismatch between the speed of technological advances in HR and the development of needed logical decision frameworks to utilize technologies. Other business areas such as finance and marketing, whose decision frameworks have developed historically and are of greater maturity, were in a better position to utilize new technological innovation in a more value-adding approach.

Minbaeva (2017, pp. 110-111) furthermore uses an analogy which distinguishes between data, information and knowledge (cf. Awad et al., 2004, p. 36-37) to explain the lack of strategic insight. While it is difficult to develop a clear separation of these different concepts, it can generally be stated that data are unorganized facts or statistics while information processes data in a way that it has meaning. Knowledge on the other hand is based on information but includes "an understanding of information based on its perceived importance or relevance for a problem area". Minbaeva then concludes that the simple collection of data and information does not lead to competitive advantage but only insightful knowledge about what drives organizational performance will increase decision-making capability.

This gap between expectations towards HR measurement and real impact can be shown with the example of the commonly used KPI 'turnover rate' i.e. the percentage of employees that leave the company during a certain period of time (cf. Dessler, 2017, p. 352). Simply measuring the number of people that leave the company, i.e. collecting raw data, does not lead to any useful insight. Combining this data into a metric and benchmarking its value against turnover rates from competitors might reveal a general tendency of whether the turnover rate is higher or lower than that of competitors, but still, this information should not be used as a sole basis for decision-making. It does not indicate whether high or low performing employees are leaving the company nor does it include the reasons for why employees are leaving and most importantly, it does not indicate what kind of impact a certain turnover rate has on organizational performance. As Becker et al. (2009, p. 6) conclude, "[…] while benchmarking might provide accessible performance metrics, there is by definition nothing strategic about them".

One of the main reasons for this is that predominantly used measures and tools such as KPIs, benchmarking and scorecards are all descriptive measures i.e. they can only depict current or historical developments but are unable to detect underlying reasons and to make reliable assumptions about the future. Naturally, companies show different levels of HR measurement approaches, i.e. while some companies are only using basic KPIs, others have highly sophisticated dashboards installed. But overall, HRM is dominated by efficiency measures, which are, as research suggests, traditionally not sufficient in the light of current challenges HRM faces in a globalized, fast-paced and increasingly competitive business environment.

The introduction of the concept of People Analytics holds the promise of changing this by breaking through the “wall in HR measurement”. The next chapter will therefore focus on the new approach of People Analytics to HRM which allows a subsequent analysis of chances, risks and implementation barriers in chapter four.

3 People Analytics: A new approach to decision-making in Human Resources

3.1 Definition and overview of People Analytics

Prior to examining the fundamentals of People Analytics, it should be first noted that the idea behind People Analytics as a theoretical concept is not totally new. In fact, Fitz-enz, as a pioneer in the area of People Analytics, initially brought up the topic way back in 1984 with his book titled "'How to Measure Human Resource Management". What is 'new' is that companies are now starting to actually recognize the importance and potential of People Analytics as stated in Deloitte's recent "2017 Human Capital Trends study" (cf. Deloitte, 2017, p. 97).

Several sources (cf. Soundararajan et al., 2017, p. 5; cf. Boudreau, 2007, p. 69) view the success story of the Oakland Athletics baseball team from 2002 as a starting point of following interest and research of using data in people decisions. In this event, Billy Beane, the manager of the team successfully relied on data analysis and statistics to identify talent needs and to scout the team (cf. Lewis, 2003).

The new interest in People Analytics is fostered by different factors. First, as discussed in chapter 2.3, HRM is experiencing an increasing pressure to improve efficiency and effectiveness of traditional HR practices as well as transforming to a more strategic role and associated herewith, demonstrate the link between HRM activities and business performance. Higher demands on HRM are based and fostered on current global trends and challenges as outlined in chapter 2.2. This development in combination with emerging technologies making it easier, faster and cheaper to collect and analyze data, which as a result leads to an exponentially growing amount of data, possibly explains the surge in interest in People Analytics (cf. Pease, 2015, p.110). As technology enables the change, some companies have started using People Analytics (see chapter 3.4) while an increasing number of companies are thinking about investing in this area, hence an analysis of the approach of People Analytics as well as chances and risks is highly relevant at this time.

Besides the term 'People Analytics' other terms, such as 'workforce analytics', 'HR analytics', 'talent analytics' or else, are also used in academic research. In general, these terms can be considered to be exchangeable (cf. van den Heuvel et al., 2017, p. 160), hence this thesis will use the term 'People Analytics' as it has become the dominant term used internationally. It should be noted that sources used in the following might use one of the other terms.

As People Analytics has only recently been increasingly picked up by literature, a universal definition of the concept doesn’t appear to exist yet. Analytics as such refers to “[...] the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and add value [...]” (Davenport et al., 2007, p. 7). Analytics is considered to be part of the broader concept of Business Intelligence which includes all kinds of processes and technologies used to systematically collect and analyze data electronically in order to support business decisions (Christ & Ebert, 2016, p. 300). The word ‘People’ in People Analytics implies the application of such tools in the area of people i.e. employees. In the simplest approach the idea behind People Analytics is to use existing as well as newly generated knowledge in order to make better, evidence-based HR decisions (cf. van der Togt et al., 2017, p. 127). Lawler et al. (2004, p. 29) furthermore argue that the goal of People Analytics is to enable HRM to demonstrate and measure the link between HR decisions and organizational performance and thus increase the value added. People Analytics should not be seen as a clearly distinguished action plan or “[...] simply a tool that produces valuable insights at the push of a button [...]” (van den Heuvel et al., 2017, p. 160) but more of a process that evolves from the general idea of addressing “[...] age-old questions with new analytical technologies [...]” (Bodie et al., 2016, p. 964).

Traditional HR reporting and metrics are normally based on internal HR employee or applicant data, such as data about demographics, employment history, educational background, performance, training and development received and data collected by employee surveys (Angrave et al., 2016, p. 3). What is new about People Analytics is the idea of integrating data from a larger variety of sources. This includes integrating data from other business functions in order to detect previously unknown correlations and patterns (Deloitte, 2017, p. 102) as well as integrating economic data. Isson et al. (2016, p. 59) sum this up by identifying three different data sources of People Analytics: talent data, company data and labor market data.

Some articles also hint the use of ‘Big Data’ within the concept of People Analytics. Therefore in order to understand People Analytics and the ways it can be used in companies an understanding of the concept of ‘Big Data’ is needed. Big Data is “[...] anything too large for typical database tools to be able to capture, manage and analyze

[...]" (Angrave et al., 2016, p. 2). Big Data is characterized by four main data characteristics: volume, variety, velocity and veracity as shown in Figure 4.

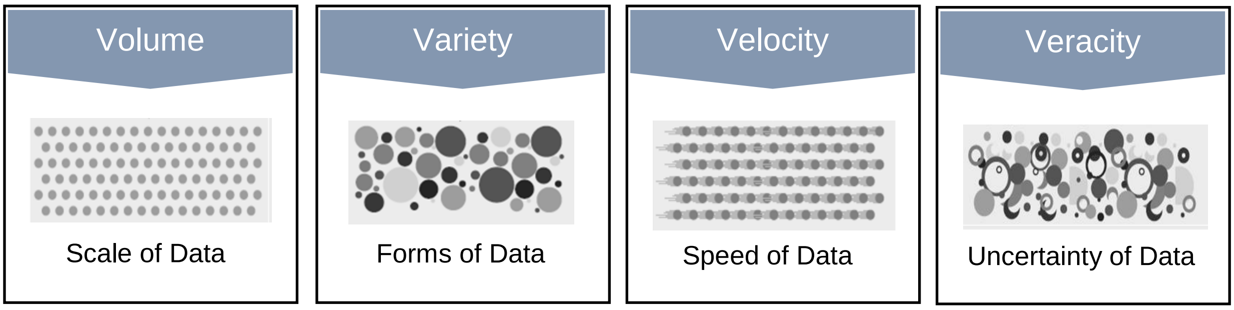


Figure 4: 4 V's of Big Data
Source: IBM, 2012, p. 4

Volume indicates the amount of data that is used within the concept of Big Data ranging from terabytes to perabytes (IBM, 2012, p. 4) while **variety** stands for the variety of data formats used (such as structured, semi-structured and unstructured data). **Velocity** refers to the speed of processing data. The fourth characteristic of **veracity** refers to the reliability of different data types as a high data quality is key when working with Big Data.

In this regard, literature has especially highlighted the possible use of a new variety of data sources related to employee's behavior as well as engagement at work (as opposed to using primarily data stored in core HR systems) (cf. Angrave et al., 2016, p. 2). Discussed are data sources such as e-mail conversations, internet history, instant messaging and social media activity. With the rapid development of sensing and tracking technology, a range of totally new possibilities of gathering data emerged. The discussion evolves around e.g. GPS signals from cell phones or vehicles (cf. Kaupins et al., 2006, p. 1) or the use of sociometers i.e. a wearable sensing device equipped with a microphone, Bluetooth and infrared receiver and motion detector (Greene, 2009). While the technological tools to integrate and combine data from both structured as well as unstructured sources are not well established yet, they are expected to evolve in the future to "[...] more fully exploit big data as it relates to HR [...]" ((Angrave et al., 2016, p. 3).

While the approach of People Analytics differs from traditional HR measurement in the way that it integrates other data sources, an otherwise clear separation is difficult to make. In order to understand why this is the case, it is helpful to look at different maturity stages of analytics.

In general, there three different maturity stages of analytics. At the lowest level of maturity are **descriptive analytics** which aim to describe current and historical data patterns as well as data relationships and answer the questions “What happened?” or “What is happening?”. They are traditionally based on efficiency metrics, dashboards and scorecards, workforce segmentation and simple data mining or correlations. Descriptive analytics form the basis for subsequent maturity levels. As described in chapter 2.4, descriptive analytics have traditionally been predominantly used by HRM.

The next level of analytics are **predictive analytics.** As the term indicates, this type of analytics moves beyond descriptive analytics by making predictions about the future based on past data patterns. They answer the questions of “What will happen?” or “What could happen?” by predicting probabilities of outcomes and their impact and for this purpose make use of a number of different techniques such as (but not limited to) neural networks, regression or decision trees.

The final maturity stage are **prescriptive analytics**. Prescriptive analytics aims at optimizing decisions by outlining different decision options and show each alternative’s business outcome. This type of analytics aims to answer the question of “What should we do?” and makes use of complex analytical methods such as simulation techniques, machine learning and artificial intelligence. While prescriptive analytics can be seen as the goal of analytics in the business area, they can still be considered an evolving approach of the future with little best practice examples (cf. Fitz-enz et al., 2014, p.3). One example frequently made in literature is Google’s self-driving car which makes autonomous decisions based on constant predictions and outcomes (Herold et al., 2015, p. 191).

Besides this three-way classification of analytics, other concepts exist. Bersin by Deloitte differentiates between five different maturity levels ranging from operational reporting to advanced reporting, advanced analytics and predictive analytics (Deloitte, 2017, S. 25) while Fitz-enz lines out five steps to climb the “value ladder” from low value reporting to relating, comparing, understanding, and at the highest value, predicting (Fitz-enz, 2010, p. 11). Nevertheless all models are united in their message that any form of advanced analytics is based on descriptive measures first (cf. Pease, 2015, p. 115). From this understanding this also means that there is no clear separation between metrics and analytics but rather a fluent transition. At the same time a common characteristic and understanding of People Analytics in literature is that it moves beyond descriptive measures and is in fact "[…] not HR metrics. It involves more sophisticated analysis of HR-related data." (Marler et al., 2017, p. 15) which is based on the belief that while descriptive data provides HRM with valuable information about the current situation, it does not deliver sufficient insight in order to successfully operate in the ever changing business environment and its challenges as described in chapter 2.2 (Fitz-enz et al., 2014, p. 5).

This also means that People Analytics is per definition not limited to certain analytical methods but makes use of the whole range from using simple time series analyses, regression analyses, correlations and clustering to more sophisticated methods (cf. Strohmeier et al., 2015, pp. 14-43). As a result "[...] an organization can be anywhere on the spectrum based on the maturity of HR processes, data quality, and capabilties available [...]" (Soundararajan et al., 2017, pp. 6-7). As stated before in chapter 2.3, HRM in the past has predominantly focused on descriptive measures and while prescriptive measures are still in its infancy, most emphasis lately has been on the use of predictive analytics for HRM (cf. Fitz-enz et al., 2014; cf. Christ, 2015).

Having analyzed the various data sources and analytical methods used within the concept of People Analytics it is important to know that any People Analytics project always starts with a business question or problem identified. As Fitz-enz et al. (2014, p. 2) put it, it is "[...] first a mental framework, a logistical progression and second a set of statistical operations [...]". Data and analytics will only lead to valuable information if they are embedded in the organizational context and address issues in HRM that are of strategic relevance.

The whole People Analytics process in general is summed up in Figure 5. Starting off with the identification of a detected business problem or question within the company, People Analytics combines and integrates data from a variety of sources using descriptive, predictive and prescriptive analytics to generate valuable actionable insights providing the link between data and business value.

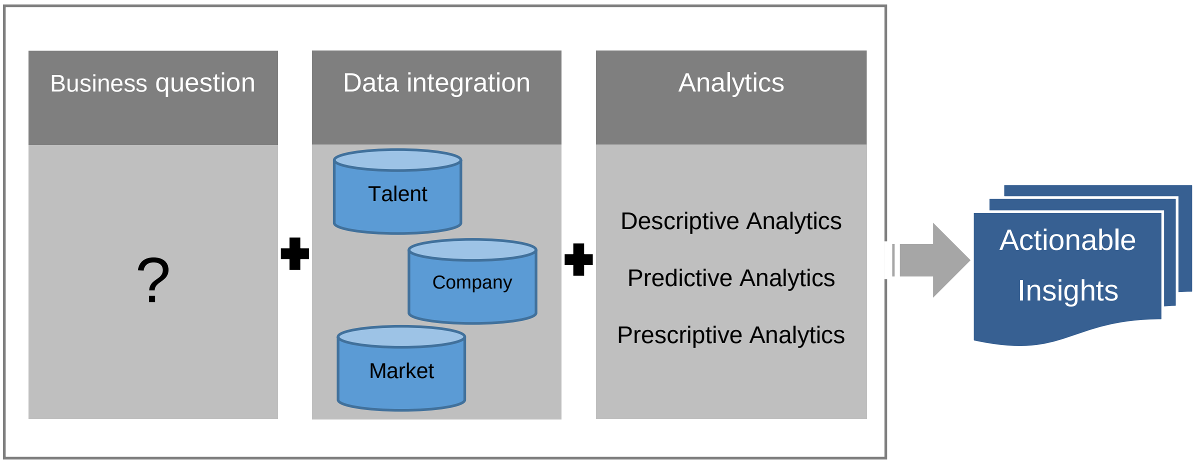


Figure 5: Process of People Analytics
Source: Isson, Jesse S., & Jac, 2016, p. 60

To determine how the process of turning data into actionable insights looks like and what kind of analytical methods have been used in the context of People Analytics so far it is most useful to look at a number of companies and the way they integrated analytical approaches in HRM. This is necessary to gain a deeper understanding of the possible impact as well as chances and risks of using People Analytics in HRM,

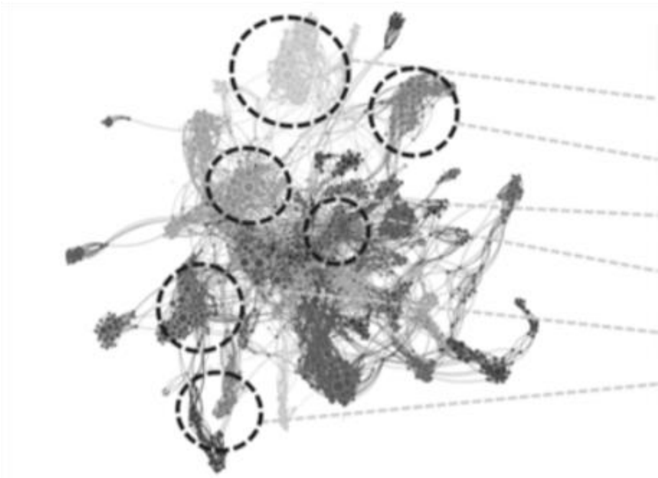
3.2 Methodology of People Analytics on the basis of business case studies

In its journey to support all business decisions with data, **Google** has been one of the first companies to make use and invest heavily in the field of People Analytics. In 2008, Google initiated the project “Oxygen”, a multiyear research initiative, to find out whether managers were actually necessary for Google’s organizational success. This research question was based on the perceived shift in the tech world to flat hierarchies as a result of changing workforce needs and values (see chapter 2.2). Especially engineers at Google were skeptical towards the need of managers as this occupational group tends to favor an autonomous workstyle as they believe that it results in the most creativity and productivity. To counter this skepticism, Google converted the research question into the opposite by asking “Are managers unimportant for organizational success?” Next Google analyzed data from employee surveys, annual performance reviews, exit interviews as well as interviews specially designed for the project to evaluate the difference between the highest and lowest performing managers. What they discovered was that managers did matter as they were able to statistically prove through correlation models that the teams at Google that were led by the best rated managers had “better turnover rates, they are happier and they report that they are more productive” (cf. Donovan, 2017).

Having established evidence that managers do have an impact on organizational performance and success, Google then shifted their research to find out what is it that those best managers are doing. Therefore a study of the differences in behavior between the best and worse managers was conducted. Again, various data sources such as performance reviews and especially also comments in the comment section of these reviews, Googlegeist which is Google’s annual survey as well as double blind interviews where the same set of questions are answered by best rated as well as worst rated managers without the interviewee and interviewer knowing what category they have been rated on. Using text mining through coding and correlating phrases, words, praise and complaints from these various data sources, Google was able to identify eight attributes a superior manager at Google possesses as well as ranking these attributes in terms of frequency that employees talked about them. Most surprisingly from these findings, soft factors such as being a good coach or communicator were rated of higher importance than having technical skills. Because Google, instead of simply using benchmarks or external studies, used their own unique data and sophisticated statistical methods to identify these eight characteristics, they were able to share this data-based list with their managers without them questioning its reliability. Building up on their research, Google is now using these actionable insights to optimize their hiring, promoting and training efforts of managers.

Google has also integrated People Analytics to improve their hiring processes within the company. Being confronted with as much as 100,000 applications per month and lengthy interviewing procedures of 15 to 25 interviews per candidate, Google looked for a way to increase efficiency as well as effectiveness of the recruitment and selection process. Therefore Google analyzed five years of interview data to determine the relationship between the numbers of interviews conducted and the ability to predict whether a candidate would be hired or not. In fact, data indicated that the ability to predict the hiring decision after four interviews was of 86 percent while the further interview rounds did not improve the predictability as much as to make up for additional time and cost spend. To prove their results, Google correlated the interview performance score of candidates after four interviews with the average score achieved having conducted all interviews. A very high correlation between the scores confirmed the findings (cf. Shaper, 2017).

Another example of using the statistical method of text mining in People Analytics has been demonstrated by **Starbucks**. Starbucks identified a business problem with turnover rates and subsequent high replacement costs. In order to analyze the reasons for people leaving Starbucks, Starbucks decided to evaluate employee's comments about the company on Glassdoor.com, a website where employees and applicants can comment on companies, using sophisticated text mining. Findings from over 5,000 comments were then grouped using clustering methods into different storylines as shown in Figure 6.



Volume score	Narrative
29	Starbucks the star
22	Grueling with a shot of great
21	Part-time pariah
12	"Ground" by middle management
10	Baristas are the backbone
6	Glorified fast food

Figure 6: Starbucks' organizational narratives
Source: Sakellariadis, 2015

Through this approach, Starbucks was able to identify that the lack of career possibilities and lack of promoting transparency by middle management were key criticism points by employees leading to reduced employee engagement and turnover (cf. Sakellariadis, 2015).

Another company that approached the problem of turnover risks with People Analytics is **Hewlett-Packard.** To understand the patterns of turnover and discover indicators for potential turnover, Hewlett-Packard initiated a pilot project applying predictive analytics on employee data such as salaries, raises, performance reviews and promotions, job rating, job rotation combined with individual turnover data for a team of about 300 employees at Hewlett-Packard. Through data analysis, Hewlett-Packard was able to develop a so-called “Flight Risk Score” expressing the likelihood to quit for each individual employee based on past employee behavior. Surprisingly the findings revealed that i.e. promotions weren’t always a positive step to decrease turnover when not combined with subsequent pay raises. After successfully reducing the turnover rate from twenty percent down to fifteen percent with the pilot group, the Flight Risk Score was then applied to the whole workforce (cf. Siegel, 2013).

One of the rare examples of using sociometers in People Analytics was established by the **Bank of America**. Driven by the question why the locational dispersed call centers throughout America achieved different levels of performance and different turnover rates, standardized work procedures, same organizational structures as well as same IT systems, same training and employees of same demographic clusters did not allow any conclusion. Bank of America then choose to take a different approach. They equipped employees of one of their call centers with wearable sociometers to track movement and communication of employees. In addition to data received from the sociometers, analysts also integrated data from e-mail communication, performance data and stress tests data as well as demographic data into their analyses. Searching for correlations between the data variables, a positive correlation between the sense of community, the stress level and performance level could be detected. The analysis was then shifted to find out what activities determine a greater sense of community and it was revealed that the employee interaction during shared lunch breaks had the biggest positive impact. Bank of America then used this actionable insight to restructure the break policy so that employees could take more and shorter shared breaks instead of staggered long breaks to increase group cohesion. As a result, turnover could be measurable decreased from 40 percent down to 12 percent and Bank of America states that they were able to retain 15 million dollars costs due to their actions (cf. Reindl et al., 2017, p. 38-43).

Xerox, a technology and service providing company, has successfully made use of People Analytic in the area of recruiting. To tackle high turnover rates in their call centers, Xerox teamed up with the analytics startup Evolv. In order to analyze the reasons behind the high turnover rates, Evolv analyzed data of current employees surrounding personality, previous professional experiences and job performance.

Through this it could be revealed that previous call center experience was not actually a good predictor of future performance as employees without previous experience showed equally high performance ratings. Additionally, employees who showed a high social media activity (meaning being active on one to four platforms) and were of a more creative personality stayed tend to stay longer with the company. Based on this actionable insights, Xerox was able to redesign their recruitment efforts shifting to a broader applicant pool and a more targeted approach. Findings have been incorporated into an initial behavioral assessment that all applicants need to take (Isson et al., 2016, p. 174).

Lowe's, an American retail company, wanted to analyze the causal link between HR measures and business outcomes in order to identify the HR measures that would have the greatest business impact. As Coco et al. (2011, p. 30) state in their article "[…] Lowe's objectives went beyond making HR more efficient or effective. Lowe's wanted to make better people decisions for the organization, not just better HR decisions." To direct the project, HR asked business leaders in the company to take part in a series of meetings to contribute their knowledge and perception of how the different business measures potentially link with each other and use the input to come up with a first data models and hypotheses to be tested in the further project. As a next step, Lowe's chose to adopt a very broad approach and thus collected HR data, marketing data, operations data as well as financial metrics which resulted in 600 data variables. Through application of correlation, factor analysis and regression, Lowe's was able to reduce the variables to the most predictive ones for each area (such as focusing on store performance and customer focus for retail). Structural equation modeling (i.e. a statistical technique that is used to test assumed correlations between variables) was applied to the first data models and after a process of rearranging, adding and eliminating variables, Lowe was able to produce a set of models demonstrating strong data correlations and causality. One of the major findings of the project was the positive relationship between employee engagement, customer satisfaction and sales volume. In fact "High employee engagement was driving four percent higher average ticket per store [...]" (p. 32). Because the HR team was able to show the causality with valid data models taking into consideration the integrated knowledge from various business areas, it achieved the credibility to act as a strategic partner for management and redirect focus on increasing employee engagement in the Lowe's stores (cf. Coco et al., 2011, p. 33).

The examples and methods described in this chapter should not be seen as a complete list but more of a snapshot of possible application areas to understand how theory translates into practice. It can be assumed that a lot of what companies are doing in the field of People Analytics is not revealed to the outside to not give away a potential competitive advantage (cf. Angrave et al., 2016, p. 4).

3.3 Areas of application

As illustrated to some extent in the previous chapter, People Analytics can be used in a variety of different HR dimensions to address different HR problems. According to a recent study by Deloitte, most emphasis has been in the areas of recruiting, performance measurement, compensation, workforce planning and retention (Deloitte, 2017, p. 97).

In their leading research article "Competing on Talent Analytics"(2010), Davenport et al. classify the various ways of using People Analytics into six manageable categories:

(1) Human Capital Facts: Analysis of key indicators for the organization's health.

(2) Analytical HR: Identification of units, departments or individuals needing attention.

(3) Human-Capital Investment Analysis: Analysis of actions having the greatest impact on business outcomes.

(4) Workforce Forecasts: Analysis of future development of the workforce and labor market to identify staffing or downsizing needs.

(5) Talent Value Model: Identification of reasons why employees decide to leave or stay with the company.

(6) Talent Supply Chain: Analysis of needed adjustment of the workforce in reaction to a changing business environment.

Furthermore Table 1 listed in the annex contains a selective overview of application areas of People Analytics based on company experience along different HR dimensions (as described in chapter 2.1) in order to get a better understanding of the questions People Analytics is able to answer. It should be noted that because Google is a pioneering company in the field of People Analytics and also the company that to this date is using People Analytics most extensively, a large part of the examples are based on Google's experience.

Future application areas are expected to rely on the increased integration of HR data with external data as well as data from other business areas targeting questions related to corporate strategy as suggested within the initial idea of People Analytics (see chapter 3.1).

3.4 Business interest and current rate of implementation

In face of global challenges, competition in the "war for talent" and current weaknesses of HRM as outlined in chapters 2.2 and 2.3, the interest of companies in People Analytics is high. In their 2017 Global Human Capital Trends report, Deloitte stated that 71 percent of surveyed companies globally[3] rated the trend of People Analytics to be "important" or "very important". This high interest is also reflected in the number of HR conferences around the world focusing on the topic of People Analytics (cf. Andersen, 2017, p. 133; cf. Rasmussen et al., 2015, p. 236), the increasing number of reports, articles and white papers on this topic (cf. Marler et al., 2017, p. 7) and the availability of technological solutions (cf. Levenson, 2011, p. 34).

At the same time, the number of companies who were able to actually successfully implement People Analytics in HRM has been described as low. Thus indicating a gap between interest in the theoretical concept of People Analytics and practical execution. Currently only some large, multinational companies reportedly have focused on and succeeded in implementing People Analytics in HRM to make better HR decisions.

A number of surveys in the past years have tried to analyze the current use of advanced analytics in companies. In a Harvard Business Review study from 2014 interviewing 230 HR professionals and business executives, 15 percent stated that they use predictive analytics based on internal or external data. At the same time 48 percent of participants stated that they would use this kind of analytics in two years (Harvard Business Review Analytic Services, 2014, p. 5). In 2015, Kassim et al. surveyed 255 European business and analytics professionals about whether European

[3] Findings are based on a survey including more than 10,000 respondents from 140 countries. (Deloitte, 2017, p. 2)

companies are following the trend of People Analytics. Results of this survey showed that the majority of participants have either started (28 percent) or are currently in the process (41 percent) to build up People Analytics capabilities while only 17 percent of participants stated that they have fully developed capabilities (cf. Kassim et al., 2015, p. 5). And Angrave et al. (2016, p. 3) state that “Although many organizations have begun to engage with HR data and analytics, most have not progressed beyond operational reporting [...]”.

Furthermore there seems to be a different rate of implementation in regards to the size of companies. The 2017 CIPD study surveying 629 HR professionals compared the usage of People Analytics in companies having up to 49 employees, up to 99 employees, up to 249 employees and equal or over 250 employees. Findings indicate that the smaller the company, the less likely the company is using People Analytics (Chartered Institute of Personnel and Development, 2017, p. 19).

As an overall conclusion, People Analytics is still considered a rather immature business discipline (Andersen, 2017, p. 134).

4 Applying People Analytics in the context of Human Resource Management

4.1 Possible chances for Human Resource Management

Supporters of the concept of People Analytics in HRM advocate that People Analytics "[...] will transform and revolutionize not only what HR does but also the impact HR will have on organizations [...]" (Andersen, 2017, p. 133) i.e. transforming HRM from its mainly administrative focus to strategic HRM (see chapter 2.1). The following chapter will critically question this assumption by analyzing potential chances on the basis of currently identified deficits of HRM (see chapter 2.3) while chapter 4.2 will focus on possible risks of applying People Analytics to HRM.

One of the current deficits of HRM identified and examined in chapter 2.3 is the way that decisions are predominantly being made based on intuition and experience which as a result leads to distorted decision making and gives rise to unconscious bias and stereotypical thinking and wrong decisions. As People Analytics provides a data-based approach to people decisions, it bears the potential to revolutionize decision-making processes. Being confronted with a changing workforce, a changing nature of work and technological advances posing current and future challenges, companies need to make sure that their HRM is fit to encounter these challenges and attract, retain, train and motivate human resources in a way that they contribute to competitive advantage as postulated in the resource-based view (see chapter 2.1). The application of People Analytics to HRM includes several chances in reaching this goal.

A first step is the achieved increased efficiency through the use of People Analytics. Although not explicitly outlined as a major deficit of current HRM practices, any efficiency gains in HRM will have a positive impact on organizational performance especially considering the fact that HRM practices often make up 50 to 75 percent of total costs of an organization (Soundararajan et al., 2017, p. 14). Once People Analytics are integrated into HRM it can be assumed that it leads to increased efficiency through saved time due to faster HR processes and faster choice of adequate HR measures and thus potentially saved costs. This is illustrated for example within the approach by Google. Through analyzing their existing hiring and interviewing processes, Google was enabled to shorten the lengthy interviewing process without losing value (see chapter 3.4) thus increasing efficiency of HRM processes.

Although increased efficiency is definitely a benefit associated with People Analytics, it does not address the real challenges of HRM as the “[...] goal is no longer mere efficiency [...]” (Harris et al., 2011, p. 4) and “Savings from making HR processes more efficient will also be relatively small” (ibid., p. 5). Increased efficiency could already be notably achieved in HRM in the last decade due to the introduction and adoption of HR technology (as described in chapter 2.4). The chance for HRM to increase effectiveness of HR measures and furthermore demonstrate the impact and link of HR actions and organizational impact is on the other hand entirely new as it could not have been achieved through commonly used HR measurement methods so far (see ‘The Wall in HR Measurement’, chapter 2.4).

In order for People Analytics to be able to increase effectiveness of HRM practices it needs to be assessed whether the use of People Analytics actually leads to better decision-making capacities of HRM and ultimately better decisions (as opposed to relying on intuition, experience and heuristics as described in chapter 2.3). Biemann et al. (2016, p. 44) provided insightful research into this topic by examining whether algorithms or people have better decision-making capabilities. By reviewing scientific studies conducted by Paul E. Meehl (“Clinical vs. Statistical Prediction: A Theoretical Analysis and a Review of the Evidence“, 1954), Grove et al. (“Clinical versus mechanical prediction: A meta-analysis.”, 2000) and Kuncel et al. (“Mechanical versus clinical data combination in selection and admissions decisions: A meta-analysis.”, 2013) they find that algorithms on average have a higher forecasting power than people’s judgements. This indicates that data-driven decisions potentially trump people’s judgements and lead to better outcomes.

With the lack of studies empirically testing this relationship and resulting increased effectiveness of decisions, evidence can (until now) predominantly be found within the different business case studies. Because Google was able to determine that managers did matter for organizational success and was able to identify core characteristics of a good manager at Google within the Project Oxygen, the effectiveness of HRM measures to train managers and promotional decisions could be improved. In a recent article from February 2018, Google states that as a result of their People Analytics project they could “[...] saw an improvement in management at Google and team outcomes like turnover, satisfaction, and performance over time [...]” (Harrell et al., 2018). Because Starbucks, Hewlett-Packard and Xerox successfully implemented

People Analytics to determine reasons for turnover and identify performance drivers they were able to increase the effectiveness of HR measures to improve retention, employee engagement and hiring decisions ultimately benefitting employee performance. Because Lowe was able to use People Analytics to prove a link between HR measures, employee engagement and store performance thus revealing that employees that were highly engaged resulted (on average) in a four percent higher customer ticket sales per store, Lowe could improve effectiveness of HR activities by redirecting them to focus on increasing employee engagement.

As a result People Analytics potentially gives HRM the needed tools to justify HR measures by being able to prove the value added with numbers just like other business functions have been doing for years.

In the opinion of Lawler et al. (2004, p. 29):

> "The use of analytics in order to understand the impact of HR practices and policies on organizational performance is a powerful way for HR functions to add value to their organizations."

In order to combat challenges imposed by a changing business environment, changing workforce and increased competitiveness for global talent, HRM needs to become a strategic partner for senior management. The reason why HRM was until now unable to be more strategic lies in the lack of valuable and actionable insights they could provide the management with. Relying heavily on descriptive measures (see chapter 2.4), HRM could only describe past situations within the workforce and HRM processes without providing causal links, reliable forecasts and justified recommendations of future actions.

People Analytics explore the roots of a perceived business problem based on data and at the same time can show the measurable impact of HR actions on success parameters – thereby demonstrating a positive relationship between People Analytics and business impact (cf. Harris et al., p. 4). In the long-term, this could enable the way for HRM to gain strategic relevance in the company as with the correct implementation of People Analytics they will potentially be able to provide management with valuable and actionable insights of the workforce. Because the methods applied within the concept of People Analytics are flexible in their approach, application areas are per definition indefinite (see chapter 3.3) and can help to combat not only current but also future challenges and workforce developments so that HRM is able to actively shape their organization's future. This is especially valuable as HRM operates in a dynamic, ever-changing business environment as described in chapter 2.2.

Because People Analytics aims to integrate talent data, company data as well as labor data, applied correctly there is a chance to break down organizational silos and facilitate exchange of knowhow inside the organization. Furthermore, People Analytics could potentially function as a risk detector for HRM e.g. warning HRM at an early stage about potential talent shortages, training needs or increased turnover (such as the 'Flight Risk Score' developed by Hewlett-Packard, see chapter 3.4) as well as external trends in the labor markets based on predictive models – the same way risk detection is used within finance to predict potential default.

Due to the fact that only few companies have successfully implemented People Analytics (see chapter 3.5), studies about the overall impact on organizational performance are not present at this time. The findings of a research report by Deloitte in 2013 indicate the impact People Analytics could have on organizational performance. It stated that those companies having integrated analytics of highest maturity (see chapter 3.1) were two times more likely to "improve recruiting efforts", "improve leadership pipelines", three times more likely to "realize cost reductions/efficiency gains" and two and half times more likely to "improve talent mobility". According to the research report these companies stock prices were on average 30 percent higher than those of the Standard and Poor's 500 over a three year time period between 2010 to 2013 (Deloitte, 2013, p. 2). Taking a broader perspective on the topic, McAfee et al. (2012, p. 63 - 64) examined the question whether data-driven companies exhibit higher performance levels. Research was based on 300 structural interviews with executives of North-American companies and showed that there was a clear positive relationship between using data-driven decision making and higher performance measures in e.g. financial and operational results.

Another deficit of current HRM identified in chapter 2.3 is the role and impact of unconscious bias and stereotypical thinking in decision-making. As outlined in chapter 2.2, companies are faced with increasingly diverse applicants as well as workforces and as such, need to make sure that their internal processes are not only fair, transparent and bias free but also designed in a way that they are able to utilize diversity to support business goals. In how far the introduction of People Analytics can be beneficial for this challenging task is currently debated. On the one hand, the point is being made that People Analytics have the power reduce unconscious biases to some extent as decisions become more and more supported by evidence. An example for this would be the development of e.g. a hiring or promotion algorithm which is able to autonomously predict which person would be the best hire or the best to promote based on past data. This would potentially reduce for example unconscious biases made in pre-screening CV's, conducting job interviews or promotion decisions (as described in chapter 2.3) as assessment can be made based on quantifiable, objective data. Furthermore, data analytics can be utilized to analyze current processes and structures with regard to indications of discrimination. Chapter 2.3 explores the effects of unconscious bias towards women referring to the „Heidi/Howard case study". Applying People Analytics could determine whether such unconscious bias are active in a company by analyzing hiring and promotion structures, differences in salaries between men and women but also between different ethnical groups and underlying reasons. Actionable insights derived from analytics can then be potentially used to eradicate differences with adequate targeted interventions.

It needs to be considered that because only few scientific research exists about the impact of People Analytics (cf. Marler et al., 2017, p. 9) or as Rasmussen and Ulrich (2015, p. 236) put it "[...] the published evidence supporting the alleged value of HR analytics is actually quite slim - it is currently based more on belief than evidence [...]", the described chances in this chapter are to a large degree still of theoretical nature that need to be proven in practice.

4.2 Possible risks for Human Resource Management

After having analyzed potential chances with the application of People Analytics to HRM, the following chapter will now focus on potential risks.

As analyzed in chapter 4.1, People Analytics provide chances for reducing unconscious bias and stereotypical thinking in decision-making. At the same time, there is also a more critical approach to this topic. In the article "The hidden bias in Big Data" (2013), Crawford proposes the question whether "[...] massive data sets and predictive analytics always reflect objective truth [...]".

The underlying problem is based on the risk that People Analytics, although aiming at reducing discrimination and biases, might potentially lead to homosocial reproduction of the current workforce demographics. Analytics can only be truly objective and bias free if the data that goes into the analysis are objective. But because data and datasets are results of a process that is steered by human decisions such as which variables should go into the analysis, how to collect data, how to analyze data and what kind of outcome is favorable or unfavorable, data and data sets can never be expected to be 100 percent objective as unconscious bias can affect the analytical results. Bodie et al. (2016, p. 1013) state that the data that goes into analytics "[...] might be skewed by the employer's own policies that may have shaped the behavior that resulted in that data [...]".

Even an algorithm learns from copying previous behavior and it is people who decide whether an algorithm should interpret certain outcomes positively or negatively. In Crawford's words: "Data and data sets are not objective; they are creations of human design. We give numbers their voice, draw inferences from them, and define their meaning through our interpretations" (2013). Examples for unintentional discrimination produced by the use of Big Data have been plenty in a variety of business areas. An example for this is the search algorithm of Google. A study examined the relationship between search entries and displayed advertisements. The results showed that the search for black-sounding names in the Google search field resulted more likely in the display of advertisements for arrest records appearing next to the results page compared to search entries for white-sounding names. The company responsible for the advertisement confirmed that there was no agreement to specifically target any ethnical group therefore the pattern could only be rooted in the search algorithm (cf. Sweeney, 2013, pp. 53-54).

Examining a hypothetical example within People Analytics, the risk of reproducing existing current workforce demographics potentially lacking diversity becomes visible. As described in chapter 3.1, predictive analytics have been to this date received most attention in the field of People Analytics. As a recap, predictive analytics tries to predict the future based on historical data. The assumption is that the model will therefore to some extent recreate the distribution found in the original data sets. This means that there is a likelihood that if data was collected during a time period when unconscious bias and discrimination were active, they will still be found in analytical predictions. Imagine a company trying to predict who in the company is likely to be a good leadership candidate. If in the past leaders were exclusively male, the likelihood that the predictive model will mirror this past development and continue to neglect women in leadership positions is high (cf. Calders et al., 2014, pp. 51-53).

Furthermore, Big Data and People Analytics are subject to their own biases as described in the article “The Bias Undermining Your People Analytics” (2013) by Dattner. He states that “[...] used the wrong way, people analytics can be just as blind and biased as human beings have always been [...]” by making reference to the so-called fundamental analytical error. This error describes the tendency of putting more value on personal factors such as character and efforts for causing performance levels and less value on situational factors such as support, constraints and context in analytics. Neglecting external situational factors, correlation might indicate that certain personality traits have a positive impact on performance levels while situational or geographical factors might actually be more accurate drivers of performance. The risk of equating correlation with causation will then lead to wrong decisions which would fail the set out aim of People Analytics to data in order to make better, evidence-based HR decisions.

Besides the risk of unintentional discrimination there is a valid risk for HRM being confronted with ethical questions of how to use the knowledge gained from People Analytics. In any surrounding, knowledge means power. Imagine HRM conducting data analytics to find out reasons for turnover. What if data shows that single people are more likely to leave the company? There is a potential risk of using that data in an unethical or even illegal way then, for example, by increasing wages or paying bonuses to single people but not to people in relationships.

As examined in detail in chapter 3.1, People Analytics is based on employee data derived from a variety of different data sources. Besides using data traditionally stored in core HR systems, discussion also involve using data from e-mail conversations, internet history, instant messaging, social media activity and data gathered from sensor technology. The examples provided in chapter 3.3 of Starbucks using text mining methods applied to data retrieved from the company rating platform Glassdoor.com to understand performance drivers, Bank of America using (amongst other data sources) wearable sociometers to analyze differing performance levels and reasons for differing turnover levels as well as Xerox analyzing social media activity of employees to detect performance indicators.

In order to be able to collect data and conduct analyses, companies need to comply with country-specific data protection regulations and therefore are always faced with a potential risk of violating such regulations. The risk is especially high for companies operating in different countries as they are likely to be faced with a variety of different, complex data privacy regulations (cf. Isson, et al., 2016, p. 298).

At the same time data protection regulations in countries such as Germany are strongly focusing on ensuring employee privacy rights. Here legislators, trade unions and works councils are monitoring the handling of data closely. Furthermore works council possesses a co-determination right in regards to many topics concerning the collection, analysis and saving of employee data in Germany (§§ 87 BetrVG). German data privacy regulation furthermore differs in regard to personal data and aggregated or anonymized data. Data is not considered personal if it doesn't allow drawing conclusions back to individuals as personal data is defined as "any information concerning the personal or material circumstances of an identified or identifiable individual (the data subject)" (§ 3 (1) BDSG, Textbuch Deutsches Recht, 2010, p. 9) . The gathering and processing of personal data is subject to stricter regulations due to the right of informational self-determination and therefore requires the approval of individuals affected (§ 4 (1) BDSG, Textbuch Deutsches Recht, 2010, p. 11). The gathering and use of data derived from social media platforms on the other hand depends whether the data is "generally accessible" (§ 28 (1) No. 3 BDSG, Textbuch Deutsches Recht, 2010, p. 36).

Of course this only reflects a small fraction of the data privacy considerations companies are faced with in Germany – and above and beyond the examples given here depending on country-specific data regulations – everywhere in the world. In addition to existing regulations, a new regulation set, the so-called General Data Protection Regulation, will be put into effect on the 25th of May 2018 across the European Union. The aim of the new regulation is to provide a "uniform framework for data protection legislation across the EU" (European Commission, 2018, p. 2). While the whole impact of the new GDPR on the application of People Analytics is hardly foreseeable at this point of time as further research is needed to grasp its implications, it will certainly add complexity to the compliance challenge and thus potentially increase costs incurred for consultancy on data regulation. Violating any data regulations can impose severe financial burdens on companies. As an example, violating against the new GDPR can result in maximum fines up to 20 million euros or up to four percent of annual global turnover (ibid., 2018, p. 19).

Independent from the risks of complying with legal data security standards is a more ethical question if it is socially acceptable to conduct such intrusive data collection and analysis even if it is legal. Companies have always collected employee data but the risk of privacy invasion is enhanced due to the variety of data sources used within the idea of People Analytics (cf. Holthaus et al., 2015, p. 679). The widespread fear of mass surveillance and related ethical implications has developed due to technological change (as described in chapter 2.1) and is considered to be a worldwide occurrence although there is e.g. the tendency of some countries to be more resistant than others. In the Deloitte 2017 Human Capital Trends study, the percentage of respondents rating People Analytics as a trend “important” or “very important” was lowest in Mid-European countries (e.g. Germany 66 percent, France 48 percent, Spain 61 percent compared to e.g. USA 76 percent, Brazil 85 percent, Indie 83 percent) which could be traced back to higher value on data and privacy matters in these countries. Negative examples of companies invading their employees privacy which have come to the public attention (such as in the case of Lidl (Connelly, 2008)) or IKEA (Clark, 2013)) have increased the fear of employees and the attention of media.

Essentially there is a risk of invading privacy of employees against their will and hence a risk of declining trust in HRM with the integration of People Analytics. A loss of trust and reputation towards HRM and company management might have potential severe impact on engagement and motivation of employees thus (in a worst case scenario) resulting in lower productivity and higher turnover as well as reputational damage if known to the public.

Another potential risk of the implementation of People Analytics involves a potential negative perception of fairness when people decisions are based on data. As outlined in chapter 2.2, companies nowadays find themselves competing in a global talent war and faced with an increasingly demanding workforce. In order to attract and retain the best talent, companies need to position themselves as attractive employers. The paradox relationship has been examined in a number of studies. Dineen et al. (2004) examined the perceived fairness of web-based applicant screening procedures.

Findings revealed that participants valued the selection process as more fair when a human screener rather than an automated decision agent was responsible for decisions. Findings should be treated with caution though due to the small sample size (= 76 participants) and the fact that the study was not conducted under real-life conditions. Furthermore the authors state that further research is needed to examine the relationship (cf. Dineen et al., 2004, p. 141).

A hypothetical question and possible risk for HRM frequently discussed in literature is whether People Analytics and the increasing use of Big Data will actually lead to a future state where personnel decisions will be exclusively made by machines and therefore posing a threat to the right to exist for HR managers. This question addresses a fundamental debate also visible in other business areas and essentially evolves around the fear that jobs will be substituted by machines. On the one hand there has been an undeniable trend in the way that advanced and smarter technology made HRM more efficient and thus substituted some HR tasks that were performed by people in the past, such as payroll. On the other hand, there is some evidence indicating that a total substitution is rather unrealistic – at least in the near future. In its journey of establishing a data-driven HRM, Google (besides successfully implementing a number of People Analytics projects as described in chapter 3.3) also had to face some failure. Trying to develop an algorithm predicting promotion decisions for one of Google's departments, Google eventually stopped the project due to resistance from managers to solely rely on black-box algorithms in making important people decisions (Biemann et al., 2016, p. 44). This phenomenon is known as the overconfidence effect in psychology or behavioral economics, a cognitive bias making people rely more on their own subjective judgement by being convinced it is better than it objectively is (cf. Kahneman, 2011, pp. 13 - 14).

Google nowadays expresses its approach to People Analytics as a way to support decision makers with adequate reliable data about all relevant factors. Therefore the once postulated mission "All people decisions at Google should be based on data and analytics" was changed now to "All people make decisions based on data and analytics" (Setty, 2014) explicitly denying the aim of substituting people with analytics or data. This being said by one of the pioneering company in People Analytics indicates that the underlying idea of People Analytics is not to take away decision making power from HRM but to support them. Still the impact of evolving Machine Learning and

Artificial Intelligence on this situation in the following years is questionable at this moment.

4.3 Implementation process

4.3.1 Implementation barriers

As analyzed in chapter 3.4, although business interest in People Analytics is high, the current implementation rate is lacking behind. The following chapter will therefore examine what barriers companies are facing in their journey to integrate People Analytics methods in HRM and second, what kind of steps or strategies can be taken to mitigate those barriers.

A number of articles have been published with regard to the reasons why companies seem to struggle to integrate People Analytics despite the chances it could bring to HRM (as analyzed in chapter 4.1). The following chapter aims to summarize the ones most frequently mentioned. Generally it should be noted that the extent of implementation barriers depend on the current and past development of companies towards becoming evidence-based e.g. companies that have already been focusing on establishing a data-driven approach and culture in the past and have proper systems in place will potentially be faced with less substantial obstacles.

Data quality and sources

The success of evidence-based decision making based on People Analytics relies to a great extent on the availability and access to accurate, valid, reliable and complete data and clear data definitions as analytics can only be as good as the data they are based on (cf. Chartered Institute of Personnel and Development, 2017, p. 18). Decision making that is based on data with insufficient data quality will therefore not deliver any value (cf. Andersen, 2017, p. 134). In the Deloitte 2017 Human Capital Trends study, only eight percent of the 3,300 participants surveyed stated that they have usable data available in order to conduct People Analytics projects thus indicating a severe readiness issue (Deloitte, 2017, p. 97). Reasons for bad HR data might be the past approach of HR to metrics and measurement as they have been more used for operational purposes than strategic purposes (see chapter 2.4) and thus the collection of HR data might lack a clear data strategy (cf. Andersen, 2017, p. 134). In an article from 2016 by Bersin, People Analytics expert of Deloitte, he stated that in his opinion the cleaning up of data can be very time and resource consuming and (depending on the current status) estimated that the process of cleaning up may take up to two years which would to some extent explain the slow implementation rate of People Analytics (Bersin, 2016).

Besides the quality of data itself, another barrier to the implementation of People Analytics in HRM is the lack of critical data sources together with a lack of available software systems and technology to gather and process data (cf. Andersen, 2017, p. 134). Depending on the current state of using HR metrics and measurement, companies are potentially faced with having insufficient software in place or having data dispersed over a multiple sources of data which doesn't allow an integration of data as postulated within the approach of People Analytics (cf. Levenson, 2017, p. 151). This is because people data has been traditionally held in a variety of different data systems depending on their use meaning there are different systems in regard to e.g. payroll, training and development, recruiting or performance. Besides technological barriers, access to data from other business areas within the company might also be hindered due to the "[...] non-central position of HR within many organizational hierarchies [...]" (King, 2016, p. 491).

Data policy and privacy issues

As mentioned in chapter 4.2, the use of People Analytics (as it involves the gathering and processing of personal data) requires an understanding and compliance with country-specific data regulations. Due to the complexity and ambiguity of some of these regulations, companies are potentially afraid of possible financial risks stirring from non-compliance with these regulations (cf. Christ & Ebert, 2016, p. 308). Furthermore, another reason for the slow implementation of People Analytics might be the fear of adverse impacts on workforce trust, motivation and productivity that the analysis of people data might potentially cause as described in chapter 4.2 (ibid.).

Lack of skills

As described in chapter 3.3, the approach of People Analytics is to use more sophisticated statistical analyses integrating talent, company and labor market data with the aim to make better, evidence-based HR decisions. Statistical methods used and discussed within the concept of People Analytics require advanced analytical skills as well as knowledge of working with analytical software and knowledge of available data warehouse of the respective company as depicted within the company examples in chapter 3.4. But furthermore a deep understanding of the business, current HR processes, available data and data security or ethical issues is needed. As Coolen et al. (2015) state: “[...] only those organizations that manage to create and maintain a balanced blend of different relevant capabilities will be successful in HR analytics”.

Research states that there seems to be a current capability gap between the capabilities needed and currently employed by HR professionals in regard to People Analytics. The 2015 Deloitte Human Capital Trends study finds that HR seems to be slow in acquiring sufficient capabilities that are needed to benefit from People Analytics (Deloitte, 2015, p. 5) and in the 2016 Deloitte Human Capital study, 62 percent of the 7,000 responses to the survey stated that see themselves weak in using Big Data in recruiting and 55 percent stated that they are weak in using people data for predictive analytics (Deloitte, 2016, p. 90).

These capabilities gaps can be potentially traced back to the notion that HR (as outlined in chapter 2.4) has traditionally not been a decision science (cf. Boudreau et al., 2007, p. 38) and has only recently began to shift the use of descriptive measures to more sophisticated ones.

Lack of commitment

Another severe barrier to the implementation of People Analytics in HRM relates to lack of commitment from management. Support from top management is considered to be vital for a successful implementation (King, 2016, p. 490). Davenport et al. (2010, p. 6) even call management commitment “[...] the single most important factor [...]” for success. And van den Heuvel et al. (2017, p. 161) state that “Most organizations, even large multinationals, lack a clear vision of the future of HR analytics within their company”. Possible reasons for this might be lack of scholarly research on this topic as well as the lack of publications of best-practice examples providing clear frameworks or roadmaps of how to successfully approach, manage and execute the implementation of People Analytics in HRM (cf. ibid.). Missing empirical evidence of the value that People Analytics might not only bring to HRM but the company as a whole (cf. Rasmussen et al., 2015, p. 236) leads to a primarily cost-oriented view on People Analytics and does not constitute a valid business case. Thus management might not be willing to redirect resources into the development of People Analytics in HRM as other projects or operating business might be more prioritized.

Implementation costs

Another barrier in applying People Analytics in HRM are incurred implementation costs. These are made up of different cost factors. Depending on the current technological equipment status, costs relate to the need of acquiring new technological solutions to be able to conduct People Analytics which can impose a severe investment and financial burden for companies. Second, the correct implementation of technology, understanding of systems, data gathering and cleaning and conducting analyses requires a lot of time and resources in terms of working hours thus also increasing implementation costs. Furthermore, depending on the current skill set of HR professionals and the workforce, additional training might be needed to develop analytical skills or even hiring new employees that possess needed skills to conduct People Analytics projects (cf. Davenport, 2010, p. 6; also cf. Shah et al., 2017, p. 375). Either way, both training and hiring costs add to implementation costs. As explained in chapter 4.2, data privacy regulations play an important role when using People Analytics. In order to understand (often complex) regulations, companies who have never conducted people data related analyses might need to engage some type of consultancy to be sure to comply with existing data regulations. Implementation costs might be especially high for smaller companies which might also be the reason for a lower current implementation rate as examined in chapter 3.4.

Resistance to change

Finally successful implementation requires the right working practices and organizational culture “[...] to underpin the use and application of data towards becoming a data-driven company [...]” (Shah, et al., 2017, p. 375). Google’s successful execution of People Analytics projects and the wide acceptance of results by the workforce can be assumed to be trace back to the established data-driven organization of Google which fundamental components is the valuation of evidence-based processes.

Companies that have not established a data-driven culture might be to some exist faced with a resistance to change impeding with implementation success (cf. Fitz-enz et al., 2013, p. 4). The introduction of People Analytics requires not only HR professionals to change their previous decision making processes but also senior managers and managers from other business functions which input is needed to gain actionable insights to give up previous belief systems. Rasmussen et al. (2015, p. 239) note that if people have invested a lot of time or effort in establishing a belief system what they believe is working best (such as relying on intuition or past experiences in decision making), then it will be very hard to convince these people of a superior approach. Again, the overconfidence effect (as previously explained within chapter 4.2) comes into play: People tend to think that their judgement is reliably greater than it objectively is and this belief can be so strong that there is even a reluctance to change when quantitative or qualitative evidence is in place (cf. Kahneman, 2011, pp. 13 - 14).

4.3.2 Implementation strategies

As described in the previous, companies are currently facing a number of different obstacles when trying to approach and implement People Analytics. The following chapter therefore aims to provide guidance and implementation strategies on how to overcome these barriers. It should be noted that the steps discussed are more of a generic nature which should be used as a first theoretical approach but of course always require adoption and case-by-case analysis to be applicable and thus do not offer guaranteed success.

Boudreau et al. (2007, p.193) laid the foundation of further implementation strategies in the field of People Analytics by establishing the so-called LAMP model or framework (as shown in figure 7) whereas L stands for the right logic, A for the right analytics, M for the right measures and P for the right process.

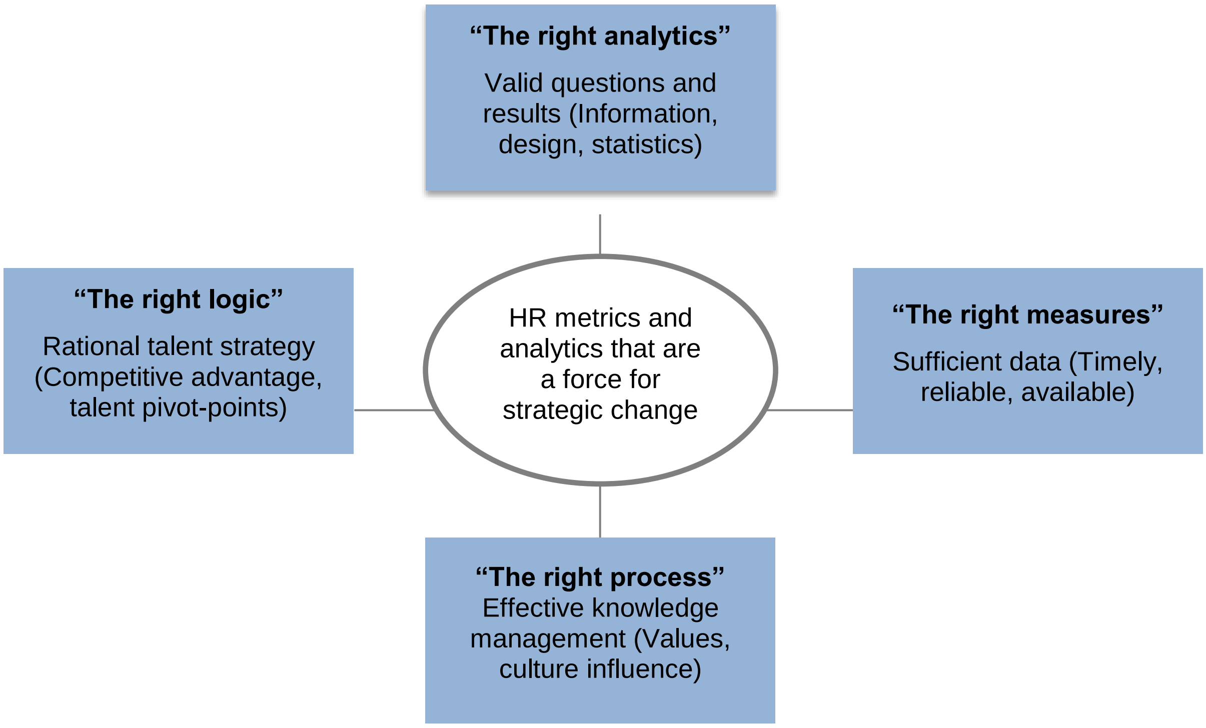


Figure 7: LAMP model

Source: Boudreau et al. 2007, p. 193

As the framework provides a more abstract approach to implementation of People Analytics, practical implications can especially be drawn from previous examined company examples in chapter 3.2.

As described within the company examples and theoretical framework of People Analytics, every People Analytics project should always start with an analysis of the most important business issues to ensure the strategic relevance of conducted data analytics (cf. Levenson, 2017, p. 148). The identified business issue should then be manifested into a clear research question to provide guidance in future project steps thus reducing time spent and increasing efficiency.

In order to gain the commitment of leadership and trust in People Analytics, it is advisable for companies to start with a small pilot project based on a business issue that is widely present to management, rather than wanting to tackle all business issues at once. If executed successfully, the business case can then be used to justify future investments by proving positive impact on business outcomes and performance.

Besides ensuring leadership commitment, it can be potentially beneficial to involve other stakeholders such as business leaders from other departments as it was done in the company example of Lowe's. Because Lowe's integrated the input of different business leaders within the company into their research design, derived results from the People Analytics were widely accepted and thus the willingness to cooperate on People Analytics projects in the future will be potentially smaller.

As outlined in the previous chapter, the lack of adequate skills constitutes a major implementation barrier. Therefore literature advises on building a multidisciplinary team within HRM thus developing a team with different professional backgrounds. Andersen et al. (2017, p. 153) propose the development of team possessing the following competencies: (1) excellent statistics and number skills, (2) strong data management skills, (3) captivating storyteller, (4) visualization techniques, (5) psychological skills and (5) understand the business.

Statistics and number as well as data management skills depend on the ambition and targeted maturity of analytics to be integrated in the People Analytics project, i.e. whether descriptive, predictive or prescriptive analytics are targeted. While these skills are related to the technical execution of data analytics, the other skills are no less important. Also highlighted by several literature sources, it is crucial for the business impact of performed data analytics to be able to report and visualize the findings in a way that it compelling to the audience which explains the need for story telling as well as visualization competencies for a successful implementation of People Analytics. This is because business leaders and management will only be willing to participate and invest in further People Analytics projects if they are not only convinced by technical outcomes and numbers but also understand the far-reaching potential that People Analytics has to offer in regard to critical business challenges. As Rasmussen et al. (2015, p. 239) put it: "This is why data and evidence from HR analytics often has little impact - it is not just about science and data - it is about activism and having a point of view, about intervention and change." At the same time, psychological skills are needed to ensure that data collected is free of unconscious bias or stereotypes thus hindering the homosocial reproduction of demographics as described in chapter 4.2 as well as ensuring that effects of overconfidence bias do not negatively impact or distort outcomes.

Data quality and access to data sources constitute major implementation barriers. In order to overcome this problem, companies should as a starting point potentially focus on the cleaning up and preparation of data to avoid inaccurate or wrong research results. Companies should start with the data that is strategically most important and needed to address the identified research question, instead of attempting to first clean up all existent data sets. Furthermore to facilitate future data gathering and handling, it will be advisable to set up standardized data definitions which "[...] provides a transparent roadmap for leaders to understand what the data means and embrace the analysis results [...]" (cf Levenson, 2017, p. 153).

To encounter the problem of employees being afraid of potential mass surveillance of their activities, an open and transparent communication with employees should be the starting point of any data gathering, i.e. "[...] making sure analytics are there for a good cause [...]" (cf. Coolen & Ijsselstein, 2015). If employees are convinced that the gathering and handling of personal data is used in their interest i.e. to improve the workplace, to achieve greater transparency and fairness and better training and development, they are potentially less likely to act with resistance and more willing to cooperate with the project.

At the same time it is important that companies understand important privacy rules and guidelines worldwide that govern the handling of personal or anonymized people data. To avoid costly implications in cases of non-compliance, sufficient time should be invested in advance of conducting data analytics, if needed with the help of an external consultant or data privacy expert.

Furthermore to ensure an ethical handling of knowledge gained from conducting data analytics (problem outlined in chapter 4.2), specific training, workshops or guidelines might provide the needed security.

5 Conclusion

5.1 Summary

At the beginning of this bachelor thesis the current deficits of traditional HRM in light of current global trends such as a changing workforce, changes in the nature of work and technology changes were identified. Focus was laid on pointing out how current HR measures are not sufficient in providing HRM with the strategic insights needed in order to react to these global challenges and thus hinder HRM in the ability to make evidence-based, effective decisions and to show the impact of HR measures on organizational performance.

In order to examine in how far the implementation of People Analytics will impact the current state of HRM, the theoretical concept and idea of People Analytics was introduced together with practical company examples which have already successfully executed People Analytics projects. Based on this knowledge, a critical analysis of chances and risks of implementing People Analytics in HRM was given as well as examining perceived implementation barriers of companies. Finally practical implementation steps were given that can possibly be used by companies interested in data analytics to overcome obstacles and lay the foundation of future People Analytics projects.

Findings indicate that the implementation of People Analytics in HRM will indeed offer great chances for tackling current deficits thus helping HRM to transform into a more strategic role as well as meeting dynamic workforce changes and increasing competitive challenges. At the same time the actual implementation rate of People Analytics in companies is still very low and People Analytics is merely viewed rather a trend than business reality. Whether People Analytics will live up to its promise of being a game changer for HRM is difficult to predict given the current research and thus will remain debatable until more companies have joined the People Analytics journey and more research has been produced regarding this topic.

5.2 Outlook

Due to the current relevance of the topic, the following chapter aims to envision possible future developments of People Analytics within HRM. A vast majority of authors and HR experts who have reviewed the topic are convinced that People Analytics is indeed not just another HR trend but will stay and grow in importance over time, thus envisioning HRM to further engage in implementing People Analytics and become more evidence-based in the future. This positive perspective on future development is reflected in the increasing amount of articles, blog posts and presentations on this topic.

On the other hand, there are also some more conservative opinions about the future of People Analytics. Some state that it is too early at this point of time to be able to precisely predict “[...] whether HR Analytics is long-lived innovation that eventually diffuses along companies to become an institutionalized HRM practice or a short-live fad [...]” (Marler et al, pp. 15-16) while others even predict that People Analytics in its current state will eventually become a management fad and “[...] fail to add real value to companies [...]” (Rasmussen, 2015, p. 236) .

The argument made is based on the observation that there has been little evidence so far on People Analytics becoming a “must have capability” (Angrave, 2016, p.1) despite the enthusiastic theoretical frameworks. Nevertheless, future development will depend to a large extent on the ability of companies to overcome outlined implementation barriers, adopt a data-driven organizational culture and willingness to invest in needed technological solutions. The rise of so-called self-service analytical software is expected to facilitate the change as it promises to be more intuitive and easier in use than existing analytics software (cf. Coolen, 2015).

Additionally, the ability to approach privacy issues i.e. balancing transparency goals and protection of sensitive employee data as well as ethical questions will potentially play a major rule in future development especially with new data regulations coming into effect.

At the same time the advancements in the maturity of analytics in form of prescriptive analytics such as Machine Learning and Artificial Intelligence will undoubtly offer even greater transformational power to HRM and thus is expected to gain not only importance in other business areas but also in HRM.

5.3 Critical acclaim

Findings of this bachelor thesis are based on current literature, relevant studies and internet sources as the topic of People Analytics has not been in the focus of academic research so far. Therefore conclusions are to a large degree derived from theoretical constructs provided by the leading experts in the field of People Analytics and only the increasing implementation of People Analytics will reveal in how far conclusions hold true or might miss crucial points. Further evidence-based research on potential chances and risks as well as feasibility studies will be needed in order to gain deeper insights. Furthermore it can be estimated that the assessed current implementation rate might be higher in reality due to companies not sharing their experiences with the public to not give away potential competitive advantage.

GLOSSARY

Anchoring bias	The act of basing a judgment on a familiar reference point that is incomplete or irrelevant to the problem that is being solved (Business dictionary, n.d.).
Algorithm	A process or set of rules to be followed in calculations or other problem-solving operations, especially by a computer (Oxford Dictionary Online, Algorithm, n.d.).
Artifical Intelligence	The theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages (Oxford Dictionary Online, Artifical Intelligence, n.d.).
Bias	Inclination or prejudice for or against one person or group, especially in a way considered to be unfair (Oxford Dictionary Online, Bias, n.d.).
Big Data	Extremely large data sets that may be analyzed computationally to reveal patterns, trends, and associations, especially relating to human behavior and interactions (Oxford Dictionary Online, Big data, n.d.).
Confirmation bias	The tendency to interpret new evidence as confirmation of one's existing beliefs or theories (Oxford Dictionary Online, Confirmation bias, n.d.).
Discrimination	Taking specific actions toward or against a person based on the person's group (Dessler, 2017, p. 683).

Diversity	The variety of multiplicity of demographic features that characterize a company's workforce, particularly in terms of race, sex, culture, national origin, handicap, age, and religion (Dessler, 2017, p. 684).
Halo effect	The tendency for an impression created in one area to influence opinion in another area (Oxford Dictionary Online, Halo effect, n.d.).
Machine Learning	The capacity of a computer to learn from experience, i.e. to modify its processing on the basis of newly acquired information (Oxford Dictionary Online, Machine Learning, n.d.).
Homo economicus/economic man	A hypothetical person who behaves in exact accordance with their rational self-interest (Oxford Dictionary Online, Economic man, n.d.).
HRM	The process of acquiring, training, appraising, and compensating employees, and of attending their labor relations, health and safety, and fairness conditions (Dessler, 2017, p. 685).
Representativeness heuristic	A common fallacy wherein people determine the probability or frequency of an event based on assumptions or past experience (Fournier, n.d.).
Stereotype	A widely held but fixed and oversimplified image or idea of a particular type of person or thing (Oxford Dictionary Online, Sterotype, n.d.).

SHRM	Formulating and executing human resource policies and practices that produce the employee competencies and behaviors the company needs to achieve its strategic aims (Dessler, 2017, p. 689)
Unconscious bias	Any distortion of experience by an observer or reporter of which they are not themselves aware (Oxford Reference, n.d.).

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Hamburg, den 09.03.2018

(Unterschrift der/des Studierenden)

ANNEX

Table 1: Current application areas of People Analytics

HR dimension	Business issues addressed with People Analytics
Analysis and design of work	**Google:** How to design the perfect team? (cf. Maier, 2016)
HR planning	**IBM:** How to connect employees to internal job opportunities? (cf. Clegg, 2017)
Recruiting and selection	**Google:** What is the optimal number of job interviews? (cf. Shaper, 2017)
	Google: What characteristics and skills should a candidate possess to be successful in a future job? (cf. Hansell, 2007)
	Maersk: What is the ROI of the company's graduate trainee program? (cf. Rasmussen et al., 2015, p. 240)
	Xerox: What is the relationship between personal characteristics as well as previous professional experience of job candidates and turnover? (cf. Isson et al., 2016, p. 174).
Training and development	**Chrysler Academy:** What is the impact of provided sales training on annual sales volume? (cf. Fitz-enz et al., 2013, p. 111)
	Harrah's Entertainment: How does the health and wellness program impact employee engagement and organizational performance? (cf. Pease, 2015, p. 122)
	Google: What are the reasons behind low performing employees and what are appropriate interventions? (cf. Pease, 2015, p. 122)
	Google: What measures can be taken to increase diversity within top management? (cf. Christ et al., 2016, p. 304)
	Google: Do managers matter? What characteristics do excellent managers possess? (cf. Donovan, 2017)
	U.S. Bank: What is the business impact of an established learning module? (cf. Fitz-enz et al., 2013, p. 94)

Performance management	**Bank of America:** How does the sense of community and the stress level of employees impact performance levels? (cf. Reindl et al., 2017, p. 38-43)
	Hewlett-Packard: What is the probability of an employee leaving the company? (cf. Christ et al., 2016, p. 305)
	Lowe's Companies, Inc.: What is the causal relationship between employee engagement, customer satisfaction and sales volume? (cf. Coco et al., 2011, p. 32).
	Maersk: What explains variance in performance between rigs and how can the attained knowledge transformed into actions? (cf. Rasmussen et al., 2015, p.239
	Microsoft: What is the impact of internal mobility on employee engagement? (cf. Green, 2017)
	Shell: What drives individual performance? (cf. van der Togt et al., 2017, p. 128)
	Shell: What drives employee engagement? (cf. van der Togt et al., 2017, p. 129)
	Starbucks: What drives voluntary turnover and employee engagement? (cf. Sakellariadis, 2015)
Compensation and promotion	**General Electric:** Which employees are most suitable for promotion? (cf. Alsever, 2016)
Employee relations	**eBay:** How strong is the adoption of the company's cultural values? (cf. Deloitte, 2016, p. 41)