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BUILDING HR ANALYTICS MATURITY

Case Study

Master's Thesis in
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ABSTRACT

The focus of this thesis is to study how organizations can develop their Human Resource (HR) analytics in order to better their readiness to provide valuable insights to support management decision-making. To strengthen its strategic role in the company, HR function must, instead of continuing to base their decisions on former experience and intuition, become more evidence and data-based. The HR function has to expand its offerings from simple reactive reporting to more advanced and predictive analytics.

This paper is a case study conducted on a large, Finnish based, multinational company, operating in the industrial goods and services –industry. The study embraces a qualitative research approach and the objective is to identify the factors effecting and also hindering the development of HR analytics maturity. Moreover, the paper seeks to figure out the current status of HR analytics in the case organization and to provide suggestions on focal areas requiring attention and actions in order to increase the HR analytics maturity.

In order to be able to produce insightful analytics from HR processes, the case organization should, first and foremost, strengthen the data culture among its HR population. Furthermore, the company should decide what it wants to accomplish with its analytical capabilities. Only after that, based on the clarified needs, the firm should start to build a HR analytics team consisting of people with different backgrounds and skills. The individuals in the team should be enthusiastic about the topic, have good intuitive skills, and be able to detect patterns in the information. At the beginning the team may conduct descriptive analytics to describe the current situation at the company. Once the team becomes more experienced and skilled it can move on to more predictive analytics to guide management's decision-making. Additionally, alongside with the assembly of analytics team, the organization should also pay attention to its data governance. In order for analytics process to function efficiently, data governance cannot be ineffective. Thus, the case organization should establish practices to guarantee the quality of data inputs used in HR analytics.

KEYWORDS: HR analytics, evidence-based HRM, HR analytics maturity, predictive HR analytics

1. INTRODUCTION

This thesis investigates the phenomenon of HR analytics in one particular multinational company (MNC). This first part of the paper presents the background and motives of the study, as well as points out the research gap in the field by shortly presenting the main findings from the previous studies. Moreover, research questions are introduced and the structure of the thesis is described.

1.1. Background of the study

Employee and workforce related insights are arguably the greatest competitive advantage for companies operating in the market where the disruption and uncertainty drive drastic changes (DiClaudio 2019). The digitalization of human resource management (HRM) has brought opportunities for human resource (HR) professionals to use the data generated by technologies to support insightful decision-making (van den Heuvel & Boundarouk 2016; Dahlbom, Siikanen, Sajasalo & Järvenpää 2019). It was proposed, already over a decade ago, that in order to enhance the quality of decisions about human capital, HR should extend its focus from the traditional service-orientation to being a decision science. With such a paradigm shift that functions like finance and marketing have already gone through, the HR function could really experience what it is like to be strategic. (Falletta 2014; van den Heuvel & Boundarouk 2016.)

Due to the fact that human behavior is considerably more complex and much less predictable compared to other tangible resources, it has always been difficult to optimize the human capital allocations (Walsh, Sturman & Longstreet 2010; King 2016). "The use of HR analytics has noticed a recent rise in popularity in response to this challenge." Through the usage of data and metrics to plan, assess, and implement new management policies, it is possible for the HR function to wean itself from using only experience, intuition, and guesswork to guide HR strategy. (King 2016.) In other words, the HR function becomes a strategic partner by providing insights gained through analytics. These insights can be used to develop competitive strategies. (Bassi 2011.)

However, the use and development of analytics in HRM has not kept pace with the organizational need. That arguably means that the strategic partnership of HR cannot be considered as self-evident. (Lawler, Levenson & Boudreau 2004.) HR analytics should go through a transformation from the basic measurement of internal HR metrics to concentre more on analyzing the critical human capital issues. It has been studied that organizations that sacrifice the needed time and effort to manage their staff as the valuable asset outrun their peer companies and achieve a competitive advantage. Even so, only a fraction of the top organizations have managed to move to Analytics 3.0, leaving most of the companies still executing analytics 1.0. (Vargas, Yurova, Ruppel, Tworoger & Greenwood 2018.)

Many HR minded people forecast a bright future for HR analytics (van den Heuvel & Boundarouk 2016). “The growth of analytical and evidence-based decision making (and the technical tools accompanying it) has great potential for improving organizational effectiveness and efficiency” (McIver, Lengnick-Hall & Lengnick-Hall 2018). Yet, like already stated, the reality today is that organizations are struggling. Companies are having difficulties to implement HR analytics into their organizational reality. It is even suggested that HR analytics represents one of the most central capability gaps in today’s HR practice. Even the large multinational companies (MNCs) do not have clear future visions for HR analytics within their organizations. (van den Heuvel & Boundarouk 2016.)

Companies lack the understanding on how to successfully use HR analytics to influence organizational outcomes. Many firms build HR analytics teams in hopes of gaining strategic insights from their people data. However, compared to other functions, the execution of HR analytics tends to fail and fall short of expectation. (McIver et al. 2018.) The challenge with HR analytics today is the lack of analyses that guide business leaders to address the top priority issues hindering the successful strategy execution (Levenson 2018). One reason behind this is most probably the lack of information on how to translate ideas into practice, as most of the literature around HR analytics is more promotional than descriptive (King 2016).

HR functions are nowadays spending considerable amounts of time and effort to produce descriptive reports after another. Descriptive reports are undoubtedly very beneficial for businesses to ensure that managers are aware of what is going on in the organization. However, descriptive reports are limited to present only snapshots of what is happening in the organization at a given time. In other words, descriptive reports lack the capability to help companies to make future predictions and they do not assist in understanding and accounting for why things are occurring in the organization. (Edwards & Edwards 2019.) If an organization wants to understand outcomes and predict possibilities and events, more advanced analytics must be applied (Fitz-enz 2010).

1.2. Research gap

The interest toward new analytical opportunities, enabled by digitalization, has increased considerably in recent years (Dahlbom et al. 2019). There has also been a huge amount of blog posts, white papers, consulting and press reports on HR analytics. Nevertheless, it seems that the topic has gained limited attention among management researchers (Marler & Boudreau 2017). It is stated that the published evidence supporting the supposed value of HR analytics is quite scarce (Rasmussen & Ulrich 2015; van den Heuvel & Bondarouk 2016) and based more on beliefs than evidence. They are also "often published by consultants with a commercial interest in the HR analytics market". (Rasmussen & Ulrich 2015.) Due to the lacking information on how to translate ideas into practice (King 2016), HR professionals have continued to work in a non-data-driven manner. (Dahlbom et al. 2019.) As a matter of fact, only a minority of organizations report effectively using HR analytics (Deloitte 2019) and even the big multinational corporations (MNCs) that have spent enormous amounts of money and resources in HR analytics and have achieved results in analytics in other areas of business admit that their HR analytics programs are stuck in reporting historical information only (Angrave et al. 2016).

Moreover, the research on HR analytics in the Nordic countries, yet alone in Finland, is arguably scarce, almost nonexistent. According to the few studies conducted on organizations operating in the Nordic countries, the topic of HR analytics is considered as very important (Deloitte 2017b; Nordic HR Study 2017), but only a small percentage of organizations report being satisfied with their HR department's current performance in it. This indicates, according to the Nordic HR Study (2017), that the need to better the performance in HR analytics is recognized, but not yet achieved among Nordic organizations. In fact, organizations are struggling to fully exploit HR analytics and are suspended in the descriptive stages of analytics. (Nordic HR Study 2017.)

1.3. Research questions and objectives

In order to better understand the ways in which data and analytics are exploited by the HR function today, and to identify the main challenges hindering it use and maturing, a case study was conducted to answer the following research questions.

The main research question in this study is:

- *What are the key-factors in building HR analytics maturity?*

The main research question is supported by the following sub-questions, guiding both the theoretical and empirical parts of the thesis:

- *What is the current status of HR analytics in the case company?*
- *What are the factors hindering the maturing of HR analytics in the case company?*

1.4. Structure of the study

This paper consists of five main chapters. The first part is introduction and it presents the topic of the thesis, its background, and the existing research gap in the field. Moreover, the aim of the study as well as the research questions and objectives are introduced. Thereafter, the paper moves on to literature review in which the prior research on the topic is presented by dividing it into smaller sections. The theory part proceeds in a “bottom-up” manner first discussing the context in which HR analytics occurs and then going deep into the topic itself and the factors affecting it. The final outcome of the literature review is the theoretical framework used in this study. The third part, in turn, introduces the methodological choices for the thesis. This part considers the research approach, philosophical assumptions, research strategy, data collection and analysis, as well as the reliability and validity of the study. The case company is also described in the third part of the paper. Thereafter, in the fourth part, the empirical findings made from the gathered data are presented and discussed. Finally, in the last part of the paper the main findings are summarized and study’s theoretical and managerial contributions are presented. The last part of the thesis also considers the limitations of the paper and gives suggestions for future studies.

2. LITERATURE REVIEW

In order to be able to answer the research questions and objectives of the study, it is important to have good theoretical base to start with. In this part of the paper the topic at hand is examined from a theoretical viewpoint, meaning the most central observations from the already existing literature are presented. The chapter starts by first discussing the more comprehensive concept of evidence-based human resource management (HRM) and thereafter moves on to view the topic of HR analytics on a more detailed level.

2.1. Evidence-based HRM

The practice of HRM has gone through significant changes over the past decades. HRM is transforming from a lower level, administrative and maintenance oriented function into a strategic business partner that is seen as a core organizational operator. (Beatty, Huselid & Schneier 2003; Ulrich & Dulebohn 2015.) One of the key factors in this transformation is the change in decision-making habits – HRM has/should become more evidence-based. (Ulrich & Dulebohn 2015.) Evidence-based practice means conscientious, thorough, and careful use of evidence from multiple sources in decision-making (Barends, Rousseau & Briner 2014). Therefore, "without rigorously tracking HR investments and outcomes, HR decisions and priorities remain whims not science." (Ulrich & Dulebohn 2015.)

According to several scholars, data processing, analyzing, and measuring are the main enablers of the strategic HRM decision-making. Business actors who succeed to manage their people resources in a more strategic manner are considerably more likely to gain greater financial returns. (e.g. Boudreau & Ramstad 2007; Walsh, Sturman & Longstreet 2010; Levenson 2018.) However, according to Boudreau & Ramstad (2007), organizations and their leaders do not always recognize the importance and potential of HR function and therefore fail to staff the department with people who posses the right know-how and talent. Instead, they still tend to rely on the traditional definition of HR's mission, which is "to be a respected business partner, helping the company achieve its goals by providing outstanding services to help manage the company's most important asset, its people". (Boudreau & Ramstad 2007: 8-9.)

In order to break out from this outdated paradigm, HR should pay more attention to the decisions it supports instead of concentrating purely on the services it provides. Derived from the aforementioned statement, the new modernized HR mission paradigm for organizations to pursue is "to increase the success of the organization by improving decisions that depend on or impact people". (Boudreau & Ramstad 2007: 9.) Ulrich & Dulebohn (2015) are on common ground as they state that it is time for HR to shift from the inside/outside approach to the outside/inside approach. This means that instead of just serving employees or redesigning and enhancing HR practices, focus should be on making sure that the services HR offers inside the company are in line with the expectations coming from the outside. (Ulrich & Dulebohn 2015.)

However, the nature of HR decision-making is challenging which makes also its strategic implementation considerably difficult. HR assets, i.e. people, differ greatly from most of the other resources a company has. That is due to their intangibility. (Walsh et al. 2010.) Lev (2001) defines an intangible asset as "a claim to future benefits that does not have a physical or financial embodiment" (Pease, Byerly & Fitz-enz (2013). Examples of intangibles in the field of HR are, among others, leadership, engagement, culture, commitment, and employer brand (Fitz-Enz & Mattox 2014: 18). It is really hard to forecast human performance and therefore it is also challenging to make strong claims about future benefits a particular employee investment has. For example, if an organization invests in a new training program, it is considerably difficult to indicate its effects on employee performance, not to mention the financial value it brings to the organization in the long run. According to Walsh et al. (2010), it is like looking through a blurry lens when trying to analyze employee's financial value for the company. (Walsh et al. 2010.)

On the other hand, costs associated with workforce are more or less clear. That combined with the fact that HR often lacks the evidence for human capital outcomes puts its initiatives in real jeopardy, as it may be treated as an expense rather than an asset (Pease et al. 2013: 4). When expenses need to be minimized, HRM practices that were approved without the support of financial measures are the first in line to be eliminated or reduced. One obvious reason behind this phenomenon is that HR professionals do not posses the analytic and data-based decision-making skills that are crucial to clarify and communicate the return of their investments. Therefore, it can be stated that it is important to pay attention to realizing the long-term benefits of people investments. (Murphy & Zandvakili 2000; Walsh et al. 2010.) "By insisting on the application of financial measures and customer data to the design and evaluation of its practices, HRM will become accountable for delivering results that are integrated with the overall business strategy" (Murphy & Zandvakili 2000). Walsh et al. (2010) agree by stating that in order for organizations to manage their investments strategically, they need to gather information and apply suitable analytics to support decision-making.

As already stated, there exists great potential for HR to became a highly valued strategic partner in organizations. However, when comparing to other more strategically mature functions like finance or marketing, HR is still struggling. (Lawler, Levenson & Boudreau 2004; Vargas, Yurova, Ruppel, Tworoger & Greenwood 2018.) Walsh et al. (2010) argue, that decisions made in HR have heavy strategic implications but because of the intangible nature of these investments, it is difficult for decision makers to quantify these implications. Yet, these whims of HR outcomes are not unbeatable. When examining e.g. the function of marketing and its nature, many similarities to HR can be found. Like HR, marketing has to deal with uncertain decision paths, involvement of psychology, and unpredictable outcomes. Still, marketing has managed to adopt tools and analytics that help the decision makers to act according to the strategy. (Lawler, Levenson & Boudreau 2004; Walsh et al. 2010.) In fact, Boudreau & Ramstad (2007) point out that finance and marketing provide HR the blueprints to become influential decision-supporting function.

Marketing, as well as finance, have both developed from professional practices (sales and accounting) into strategically important decision sciences. Thus, a pivotal solution for HR is to do the same and transform into a decision science: talentship. (Falletta

2014.) (See **Figure 1.**) According to Boudreau & Ramstad (2007: 19-20), this is simply about improving the decisions about the talents of people and how they organize and interact. However, Falletta (2014) states that, for HR, there is still a long way to go, as it is still very common in organizations to use information and data to support decisions that are already made. According to him, with the help of information and data companies should rather question the path they are on when it comes to HR strategy and planning. In other words, in order to really adopt an evidence-based approach, the data and information used in decision-making should be transformed into analytics, and further on into meaningful HR intelligence. (Falletta 2014.)

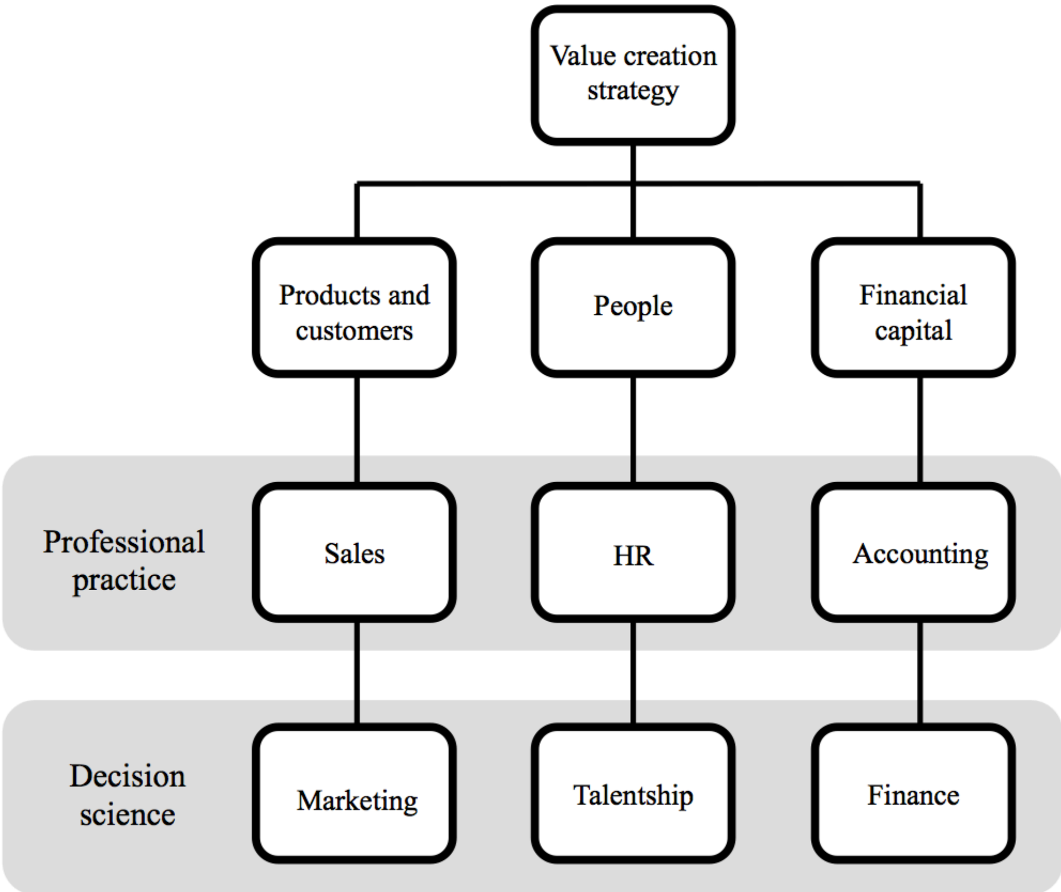

Figure 1. From a professional practice into a decision science (Adapted from Boudreau & Ramstad 2004: 18.)

HR intelligence is defined as "a proactive and systematic process for gathering, analyzing, communicating and using insightful HR research and analytics results to help organizations achieve their strategic objectives" (Maldonado 2014). In other words, HR intelligence builds upon both scientific evidence and analytics, thus being supported by empirical as well as theoretical research. According to Falletta's (2014) value chain (see **Figure 2**), HR intelligence can be seen as an opposite to intuition and prior experiences. As already stated, HR decisions have tended to lean to prior experiences and prior knowledge. Nowadays emphasis should be on basing decisions more on predictive analysis and scientific evidence. (e.g. Ulrich & Dulebohn 2015.) However, it is important to see HR intelligence both as a science and art, meaning that intuition and expertise should not be completely forgotten. (Fitz-enz 2010: 4-5; Falletta 2014; King 2016.) In addition, it is essential to mention that the concept of HR intelligence is used interchangeably with terms such as "evidence-based HR", "HR decision science", "workforce analytics", "talent analytics", and "HR analytics" (e.g. Fitz-enz 2010; Falletta 2014). Today, the most used term is arguably "HR analytics" and due to its popularity, it is used also in this paper.

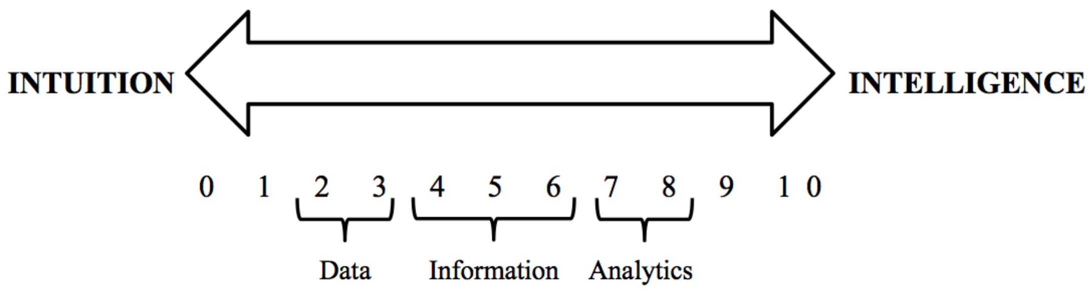

Figure 2. The HR intelligence value chain (Adapted from Falletta 2014.)

As can be seen also from **Figure 2.**, a mature decision science highlights the importance of data, information, and analysis and aligns them with its framework principles. Despite of the existing advanced technology, data availability, and the competences to distribute and report information, HR is still facing a huge challenge to master the creation of strategic insights that drive the organizational effectiveness. (Boudreau & Ramstad 2007: 37-38.) Next in this paper, in order to build a solid theoretical base for HR analytics, the concepts of data, measuring, and metrics will be discussed separately.

2.1.1. From data to big data

The world has gone through significant changes as technological advancements have altered the way we live and work (Abdulmelike 2017). Organizations are expected to more and more handle and manage challenges concerning strategic capability as well as trends in how employees, stakeholders, and customers communicate and want to engage with one another. Aforementioned observations with continuosly increasing market and competitor demands, advocate the need for organizational changes. (Shah, Irani & Sharif 2017). Companies are, as a matter of fact, in increasing numbers, embracing the new world of smart working, business analytics, and increasing volume of data (Abdulmelike 2017). McAfee & Brynjolfsson (2012) even claim that data-driven decisions are simply better decisions. They agree with the ideas and opinions presented in the previous section of the paper by stating that data, and especially big data, helps managers to make decisions based on evidence rather than a hunch. (McAfee & Brynjolfsson 2012.)

There are two ways to view data: structured and unstructured. Structured data refers to financial data while the term unstructured data is used when discussing economic or less tangible data. Examples of financial data are cash and other liquid resources, like stocks and bonds. Economic data, also called as off-balance sheet assets, on the contrary includes things such as market reputation, customer satisfaction, and community relations. These two forms of data are very distinct but yet they eventually blend with one another. That is because every economic data item should, at some point, turn into financial value. Financial value is reached when, for example, a stakeholder invests in the company stock, a customer acquires a product or service, or a talented employee applies for a position in the company. (Fitz-enz & Mattox 2014.)

In todays world, technology is assisting to generate data so efficiently and fast that new words have to be invented in order to be able to describe the scale. Instead of megabytes and gigabytes, the storage capacity of data is nowadays expressed in exabytes and zettabytes. (Fitz-enz & Mattox 2014; Abdulmelike 2017.) This presence of large volume of data with huge variation generated in today’s digital environment is referred as big data (Abdulmelike 2017). There exists multiple definitions for big data in the academic literature (Shah et al. 2017), but one often cited report defines it as “anything too large for typical database tools to be able to capture, store, manage and analyze” (Angrave, Charlwood, Kirkpatrick, Lawrence & Stuart 2016). Similarly, Grable & Lyons (2018) describe big-data as large data sets that are collected by organizations and governments. According to them, these data sets are so excessive that traditional data processing methods are not enough to make sense of the data. When analyzed in appropriate manner, “big data can provide more precise insights into hidden patterns, trends, and associations, especially in the context of human decision making”. (Grable & Lyons 2018.)

Furthermore, big data can be defined in terms of volume, velocity, and variety. Volume refers to the total size of the data set, while velocity represents the speed at which the data is acquired and generated from both internal and external sources. Nowadays, due to the developments in computing power, the volume of collected data keeps on growing, as storing causes no limitations. Data is also gathered today in real time at a very fast pace. Finally, variety, or as Shah et al. (2017) call it, variability of data refers to the types of data being collected. Nowadays big data takes the form of e.g. social media messages, updates, and images, sensor readings, as well as phone GPS signals, while couple decades ago it was only basic demographics data, attitudes and opinions, and geographic information. (McAfee & Brynjolfsson 2012; Shah et al. 2017; Abdulmelike 2017; Grable & Lyons 2018.)

In addition to the original three Vs, new ones have been added later on. A most discussed of them is veracity. Veracity, according to Grable & Lyons (2018), refers to the “noise” in the data. In other words, veracity presents “the varying credibility and reliability of different data sources” (Abdulmelike 2017). Simsek, Vaara, Paruchuri, Nadkarni & Shaw (2019) mention also vision, visibility, and value as considerable dimensions of big data. According to them, each dimension offers its own challenges, but also ways to conquer them, in accessing, storing, and using big data. For example, when it comes to the velocity dimension, issues such as transfer speed and storage scalability arise. Veracity, in turn, is associated with matters related to uncertainty, authenticity, trustworthiness, and accountability. (Simsek et al. 2019.)

As stated already, big data refers to a set of data that is too extensive to be managed and analyzed with basic database tools (King 2016). Capelli (2017), in turn, even argues that there is no such thing as big data in HR. According to him, in most organizations HR is still struggling to use data at all – not to mention big data. He explains himself by noting that the headcounts in companies are usually thousands, not millions, which literally does not fulfill the traditional definition of big data. (Capelli 2017.) However, recently the definition of big data has concentrated more on the smartness of data rather than the size of it. In other words, smartness of data refers to "the extent to which it is able to provide the material to conduct fine-grained analysis that successfully explains and predicts behavior and outcomes". (King 2016; Angrave et al. 2016.)

This new way of seeing and defining big data is arguably suitable in the field of HR as it embodies the data held in human resource information systems (HRIS). Data held on HRISs is considerably small by the standards of large unstructured data. However, it is big when viewed as quantitative data sets, and also able to produce smart insights due to its longitudinal nature. Therefore, it is possible to conclude that analytics include aspects from both the traditional as well as the updated interpretation. In other words, analytics consists of "traditional relational database and spreadsheet-based analysis, new forms of database software that allow very large quantities of data to be stored and organized more efficiently, and new techniques for representing and understanding data through visualization". (Angrave et al. 2016.)

However, the technical ways to fully integrate, organize, and analyze the data stored in traditional HRISs together with the data from the aforementioned large unstructured data sources is not yet established. Also topics such as privacy, consent, and ethics cause issues when dealing with HR related big data. (Angrave et al. 2016.) As a matter of fact, in most organizations HR's data-driven procedures are still limited to means like collecting people metrics, exploiting comparison benchmarks, reporting to management, and getting rid of manual efforts by automating the reporting processes (HBR 2013).

Still, there is a lot organizations can achieve with already excisting relational data that is stored in HRISs. Today's data-driven actions can be seen as crucial groundwork for more advanced and exact analytical use of big data and the enabler of data/evidence-based human capital decisions. Furthermore, in the future, when an organization is ready to move from basic descriptive data usage to more predictive modeling, it will have enough historical data to construct models on. (HBR 2013). According to Angrave et al. (2016) there are two central questions that should be considered in organizations when it comes to big data in the context of HR. Firstly, it is important to ask how analytics can be utilized to create, seeze, leverage, and protect the value within HR data. The second question, in turn, asks what are the ways and what is needed for excisting, essentially descriptive, analytics to evolve into programmes that are more strongly focused on measuring and modelling the strategic impact of workfore inputs in order to offer better decision tools for management. (Angrave et al. 2016.)

2.1.2. HR metrics and measuring

Like already pointed out, as the importance of human capital in today's business world is increasing at a rapid pace, there is a great opportunity for HR to become a core organizational function and participate in the development and implementation of the corporate strategy. However HR is still struggling to prove its worth and has failed to truly achieve the status of a strategic partner. One pivotal reason behind it is the fact that HR has not managed to acquire the needed level in analytic and data-based decision-making capability. This, in turn, stems from the lack of right and suitable metrics and analytic models. Unlike marketing and finance, HR tends to be unsuccessful in providing metrics that guide and assess HR processes and practices from a strategic viewpoint. (Lawler et al. 2004.) As a matter of fact, HR has been described as a soft function. The softness refers to the idea that people and metrics do not necessarily blend together. (Feather 2008; Tootell, Blackler, Toulson & Dewe 2009.)

According to Dulebohn & Johnson (2013), all core business functions use metrics. Therefore, if HR wishes to consolidate its position as part of that group, metrics need to be applied. (Dulebohn & Johnson 2013.) This does not come as a surprise, given also the unforeseen growth of human capital related data and different measuring and evaluation practices, stemming from the increasing interest towards people as organizational assets. Also the rapid development of HR systems, that have enabled the more efficient and quick data gathering and management, has supported this trend. To avoid risks associated with this kind of direction of development, HR must have the right frameworks applied to support and guide data analysis and decision-making. (Boudreau & Ramstad 2002.)

Like Rasmussen & Ulrich (2015) point out, “rigorous analyses of loads of data on the wrong questions often have little practical value”. Mclver et al. (2018) say that it is crucial to be able to ask data the right questions and subsequently base the right metrics on the answers. Feather (2008) agrees when she says that HR has to ask itself what should be measured. According to her, without a measurement framework these huge amounts of collected data can become “an exercise in measurement for measurement’s sake”. (Feather 2008.) Boudreau & Ramstad (1998) are on a common ground as they note that HR measurement systems should systematically link to organization’s strategic goals and embody the “theory of the firm”, which refers to the linkage between people and organizational performance.

Dulebohn & Johnson (2013) define a metric as “an accountability tool that enables the assessment of a function’s results”. According to them, in the field of HR the fundamental idea has been that through metrics HR can strengthen its partnership with other core functions by building a business case for their work. (Dulebohn & Johnson 2013.) Marler & Boudreau (2017) agree by characterizing HR metrics as “measures of key HRM outcomes”. In the academic literature, metrics are often theorized also through the different types of existing measures. Scholars have identified multiple categories for HR metrics, from which the most discussed ones are: *efficiency, effectiveness*, and *impac*t metrics. (E.g. Lawler et al. 2004; Tootell et al. 2009; Dulebohn & Johnson 2013.)

The efficiency metrics/measures concentrate to shed light on how well the HR function succeeds in its basic administrative tasks. In fact, until this day, most of the developed

HR metrics have been efficiency measures (Dulebohn & Johnson 2013). They focus heavily on productivity and cost, which arguably makes them the easiest kind of metric in terms of data collection. Good examples of efficiency metrics are, among others, cost per hire, days to fill a position, HR expenses per employee, and the percentage of performance reviews completed on time. (Lawler et al. 2004; Dulebohn & Johnson 2013; Carlson & Kavanagh 2018.) Efficiency metrics are operational in nature and therefore they alone are not enough. In order to measure the effectiveness, quality, and impact of HR operations on a larger scale, supplementary metrics are needed. (Dulebohn & Johnson 2013.) Lawler et al. (2004) agree by stating that many efficiency-focused metrics are limited, as they tend to ignore "the issues of service quality and impact of HR services on organizational effectiveness".

Effectiveness measures are less familiar to organizations than the ones belonging to the efficiency category (Tootell et al. 2009). HR effectiveness metrics (also called as "cost benefit metrics") consider and measure whether HR programs and practices have managed to affect the targeted people or talent pools as intended. According to Dulebohn & Johnson (2013), these metrics typically include measures of the strategic skills and core competencies owned by the staff. Also, with the help of these metrics it is possible to assess how well and successfully critical positions are filled and what kind of actions and activities there are in place to develop talent. (Dulebohn & Johnson 2013.) Lawler et al. (2004) note that HR is often seen as responsible for acquiring, developing, and deploying talent in organizations. Through measures of talent quality, talent development, and talent deployment it is possible to monitor and assess how well the function has succeeded in its commitments. This is important also from the strategic perspective. An organization is destined to fail if its strategy has false assumptions about firm's ability to fill critical positions and develop pivotal areas of expertise to support the strategy execution. (Lawler et al. 2004.)

Impact is the third and highest level of HR metrics. This level is also called as strategic HR metrics (Dulebohn & Johnson 2013) and it explains in measurable terms how HR has managed to impact business outcomes in respect of finance, customers, processes, and people. In other words, in this context impact refers to the linkage between HR operations and organization's competitive advantage. These strategic HR metrics help to decide where to allocate and how to manage human capital resources in order to gain and sustain competitive advantage. According to Lawler et al. (2004), to be better able to guide these kinds of decisions, impact metrics tend to integrate HR data with other organizational data. HR function's effect on operational effectiveness needs to be proved by demonstrating a connection between a specific HR metric and other metrics in the organization. (Lawler et al. 2004; Dulebohn & Johnson 2013.)

Efficiency	Effectiveness	Impact
Number of open requisitions	Quality of hire	Length of stay
Number of hires	Quality of the recruiting process	Monthly productivity
Hires by level	Quality of service from recruiter	Improved cycle time in job
Hires by business unit	Fit with the job	Contributions to customer satisfaction
Average cost per hire	Fit with culture	Contributions to quality
Amount of coaching received	Employee engagement	Improved project quality
International assignment	Ability to coach	Improved efficiency
Mobile workforce	Ability to be coached	Increased cost savings

Table 1. Examples of efficiency, effectiveness, and impact metrics (Adapted from Fitz-enz & Mattox 2014: 133-134.)

In addition to these three aforementioned levels of HR metrics, Dulebohn & Johnson (2013) have defined also a fourth one: *Human capital metrics*. These metrics, as the name suggests, try to measure the value of human capital. The fact that organizations do not own their employees makes this a hard and difficult task. Workforce, unlike other capital assets, does not have precise documented purchase price or market value. Instead, the amount, type, and worth of human capital changes over time as people acquire new skills and get better in their areas of expertise. Given that the importance of human capital in today's business world is constantly increasing (Boudreau & Cascio 2017), it is no wonder that firms attempt to show their value in quantifiable terms. (Dulebohn & Johnson 2013.) Examples of human capital metrics are presented in the following table. (See **Table 2.)**

Human capital metrics	
Expense factor	$\frac{\text{Operating Expense}}{\text{Total Full-time Equivalent (FTE)}}$
Profit per employee	$\frac{\text{Revenue} - \text{Operating Expense}}{\text{FTE}}$
Labor cost factor	$\frac{\text{Compensation + Benefit Costs}}{\text{FTE}}$

Table 2. Examples of human capital metrics (Adapted from Dulebohn & Johnson 2013.)

Even though there exists a consensus about the importance of HR metrics in transforming HR into a strategic partner, surprisingly many companies still admit using only efficiency metrics. In other words, in most cases companies are not even trying to develop HR effectiveness metrics, and even fewer are measuring the impact on the organization. Nevertheless, companies that assign resources to data gathering in order to apply metrics are arguably more likely to "develop predictive models that will contribute to sustained competitive advantage in managing and deploying their talent". (Dulebohn & Johnson 2013.) It is important, however, to understand that metrics are just means of measuring something. The attention should be on that something instead of the metrics themselves. Nowadays, instead of just measuring the efficiency and effectiveness of the HR function, HRM should rather measure and figure out how much value it produces for the overall business. (Ulrich & Dulebohn 2015.) Also, it is good to keep in mind that there still exists definitional ambiguity in the literature between the terms of HR analytics and HR metrics. According to Marler & Boudreau (2017) HR analytics are not HR measures or metrics, but rather "statistical techniques and experimental approaches" used to show and prove the outcomes of HR procedures. (Marler & Boudreau 2017.)

2.2. HR analytics

Rest of the literature review delves into the main topic of the paper; HR analytics. Firstly, based on the already existing literature, the concept of HR analytics is defined and discussed. Also, the levels of HR analytics and analytical maturity are presented. Thereafter, the identified five key-factors effecting HR analytics maturity are each considered and discussed separately. Finally, as a result of the literature review, a framework for the study is formed.

2.2.1. Defining HR analytics

Nowadays, in order to better understand their workforce and make wiser decisions, HR and business executives have understood the importance of data analytics. Even though accessing HR data has become increasingly easy in the last few decades, the HR analytics movement is still relatively new. (Subramanian 2017.) Marler & Boudreau (2017) challenge this notion by claiming that analytics in HRM has been around for years. According to them, notions of measurement in human resources can be tracked as far as the beginning of 1900s and the first book on the topic was published already in 1984. Therefore, it can be argued that the topic has been around for years but has gained a lot more attention in recent years. However, despite the huge interest around the human capital analytics, the majority of organizations nowadays find it challenging to evolve from operational reporting to analytics (Boudreau & Cascio 2017).

Analytics is stated to be a necessity for the HR function. Analytics acts as a tool for the function to create value from people and to strengthen its strategic influence in the organization. (Angrave et al. 2016.) Even so, no universal definition exists for HR analytics. In fact, according to Bassi (2011), the term “HR analytics” means distinct things to different people. Some people may see it as a process of systematic reporting using a selection of HR metrics while some believe “the only activities and/or processes that constitute HR analytics are those that involve “high-end” predictive modeling”. Both of these viewpoints are limited and present only separate components of HR analytics. (Bassi 2011.)

Analytics can be seen to have developed in the crossroads of engineering, computer science, decision-making and quantitative methods. It is a discipline to organize, analyze, and understand the continuously increasing amounts of available data. (Angrave et al. 2016.) HR analytics, in turn, is a domain in the larger field of analytics applying analytic process in the organization’s human resource department. The aim is, in addition to gathering data on employee efficiency, to provide insights “into each processes by gathering data and then using it to make relevant decisions about to improve these processes”. (Chattopadhyay, Biswas & Mukherjee 2017.) Fitz-enz (2010) points out that analytics, like often assumed, is not all about statistics but rather it is a meeting point of art and science.

The ideas behind dividing the field of analytics into two camps are that even though statistics play a major role in analytics, it is even more crucial to first understand the relations and interactions of the problem’s elements. “Analytics is first a mental framework, a logistical progression, and second a set of statistical operations.” (Fitz-enz 2010: 4; Ftz-enz & Mattox 2014: 3.) Baesens, De Winne & Sels (2017) agree as they diagnose that analytical HR models should do more than concentrate on statistical performance. According to them, two other important factors to consider are model interpretability and compliance. Interpretability means that every HR decision made using the help of analytics should be thoroughly argued and, if necessary, easily explained to parties involved. Compliance, in turn, highlights how important it is to use caution when interpreting analytical models. Also, gender equality and diversity are dimensions that should be treated with respect when gathering and selecting data to be used in the analytical HR models. (Baesens, De Winne & Sels 2017.)

Fitz-enz & Mattox (2014) further describe HR analytics as a communication device. They see it as way to bring together data from distinct sources, like surveys, records, and operations, to best describe the current situation and conditions as well as the probable futures. Thus, HR analytics can also be described as an evidence-based approach helping organizations to make better decisions. (Fitz-enz & Mattox 2014.) However, it is crucial to understand that analytics itself does not bring value to the function or the whole organization. Instead, analytics needs to be linked to business strategy to be valuable. (LaValle, Lesser, Shockley, Hopkins & Kruschwitz 2011.) Rasmussen & Ulrich (2015) are on common ground as they advice that analytics for the sake of analytics is not helpful. They bemoan that instead of focusing on the business challenges, analytics today tends to start with data. That contradicts with the fact that HR becomes successful by contributing to business decisions. Instead of just validating the already existing information and knowledge, HR should also try to act as an informant in business decisions. (Rasmussen & Ulrich 2015.) This links with the already discussed idea of moving from inside/outside perspective to outside/inside view (Ulrich & Dulebohn 2015). According to Rasmussen & Ulrich (2015), it is important for HR to move the focus from doing things right to doing the right things.

Additionally, when trying to define HR analytics, the existence of multiple overlapping terms can cause confusion. For example, terms like workforce analytics, people analytics, and talent analytics appear in the literature and are often used interchangeably. (Van den Heuvel & Bondarouk 2016; McIver et al. 2018.) According to McIver et al. (2018), despite the term used, in the end it is about "the analysis of HR-related data, but also the integration of data from different internal functions and even data external to the firm". Van den Heuvel & Boundarouk (2016) are somewhat in disagreement with them, as they believe that the differences in labeling go beyond basic semantics. In their opinion, for example the term HR analytics may suggest that it is the HR department who is mainly responsible for identifying and quantifying people drivers of business outcomes. The term "workforce analytics", in turn, is somewhat separated from the HR department and falls more on the shoulders of the whole organization. However, the term has a bit exploitative connotation to it. A more employee friendly alternative would be the term “people analytics”. (Van den Heuvel & Bondarouk 2016.) Nevertheless, in this paper the term “ HR analytics” is used, as it seems to be the most neutral option. Furthermore, this paper leans to the following definition of HR analytics:

> *“The systematic identification and quantification of the people drivers of business outcomes, with the purpose to make better decisions.”* (Van den Heuvel & Bondarouk 2016.)

Even though, there has been a lot of discussion around the topic of HR analytics and people have identified the opportunities and benefits it can offer, organizations are still struggling to adopt it. In a study conducted by Deloitte (2015), HR analytics is, in fact, identified as one of the biggest challenges in HR practice nowadays. (Van den Heuvel & Bondarouk 2016.) The fact that workforce has gone through significant changes in recent times causes the need to manage it more efficiently. The staff in organizations today is more and more versatile covering many generations and continents. Still, it is customer, marketing, and financial analytics in organizations that are invested in. Firms should really ask themselves why the same approach has not been taken with their arguably largest and most crucial asset, workforce. Investing in HR analytics is not actually beneficial only to the HR function but serves other business areas as well. “By providing people analytics and insights to other areas of the business through an information loop, HR can help drive business value.” (Deloitte 2018.)

Along with all the criticism, Edwards & Edwards (2019) have also seen development in the field of HR analytics. According to them, in recent years the attitudes towards HR analytics have changed considerably. Instead of being something new and attractive, HR analytics is nowadays considered to be almost a necessity in the offering of a HR function. (Edwards & Edwards 2019.) In fact, in a survey conducted by Deloitte (2018), 71 percent of participated executives identified HR analytics as important or very important. Unfortunately, organizations have not yet been able to show their conviction in practice. Instead, firms are stuck in producing descriptive reports after another. There is no question that descriptive analytics would not be useful but the truth is that there are certain limitations. These descriptive reports only tell what is going on in an organization at a given moment without having anything to say about, for example, reasons behind the occurring events. Furthermore, descriptive analytics does not predict possible future outcomes at all, which is arguably the most notable factor differentiating predictive HR analytics from the analytics currently carried out by most organizations. (Edwards & Edwards 2019.) These different levels of HR analytics are presented and discussed next.

2.2.2. The levels of HR analytics

HR analytics is divided into three different levels: *descriptive, predictive*, and *prescriptive* (e.g. Fitz-enz & Mattox 2014; King 2016). Descriptive analytics refers to the inspection of data and information in order to figure out what is going on in an organization at a given moment or what has happened in the past. In other words, it reveals and describes relationships and presents historical data patterns. (Fitz-enz & Mattox 2014; Sivarajah, Kamal, Irani & Weerakkody 2017.) According to Fitz-enz (2009), descriptive HR analytics offers also a way to drill down into the workforce to discover subgroups based on predetermined traits. He states that, this kind of workforce segmentation corresponds to customer segmentation done in the field of marketing. (Fitz-enz 2009.) Today, majority of organizations are still on the first level carrying out very basic descriptive HR analysis (Minbaeva 2017). Even though descriptive analytics brings less value to an organization than higher-level analytics, it is a prerequisite as it acts as a foundation for more advanced analytics. Examples of descriptive analytics are, among others, dashboards and scorecards, data mining for basic patterns, human capital segmentation, as well as periodic reports. (Fitz-enz & Mattox 2014.)

The second level of analytics is the predictive analytics. There are three factors that have caused the predictive analytics to become a hot topic in HR. First of all, computing power has developed significantly and become more affordable. Secondly, because of cloud storages, more and more big data is available for HR to process. Finally, nowadays there is a global war on talented employees, which is why organizations need to protect and pursue talent streams. (Mishra, Lama & Pal 2016.) Predictive analytics, unlike descriptive analytics, is about trying to determine the future with the help of current and historical facts (Sivarajah et al. 2017). So, predictive analytics gives meaning to the aforementioned patterns for future. It is about probabilities and potential impact. (Fitz-enz & Mattox 2014.) Predictive analytics includes statistical techniques, machine learning methods, and data mining models that are used to analyze and extract current and historical data and facts to make predictions about the future (Mishra et al. 2016). Examples of predictive analysis are decision trees, genetic algorithms, and neural networks (Watson 2015).

As already noted, in predictive analytics the future is expressed with the help of probabilities. However, it is important to understand that these kinds of analytical predictions cannot be made with absolute certainty. It is possible to foretell the future only to some degree. (Fitz-enz 2009.) However, in order to achieve the highest possible degree of probability in forecasts, the following four things must be in place (Fitz-enz 2010).

1. A full comprehension of current and historical events.
2. An understanding of present trends and the drivers behind them
3. The ability to recognize consistency and change patterns
4. The availability of tools to describe the future probabilities

The third and final level of analytics is prescriptive analytics. According to Fitz-enz & Mattox (2014), “prescriptive analytics goes beyond predictions and outlines decision options and workforce optimization”. So in other words, it predicts future outcomes based on complex data analyzes and provides decision alternatives and possible future outcome options. (Fitz-enz & Mattox 2014.) King (2016) describes prescriptive analytics as designing treatments to overcome currently occurring obstacles. Analysis at this level is very rare in HR (Fitz-enz & Mattox 2014). Even the organizations considered as pioneers in analytics have very seldom managed to master this advanced analytics (King 2016).

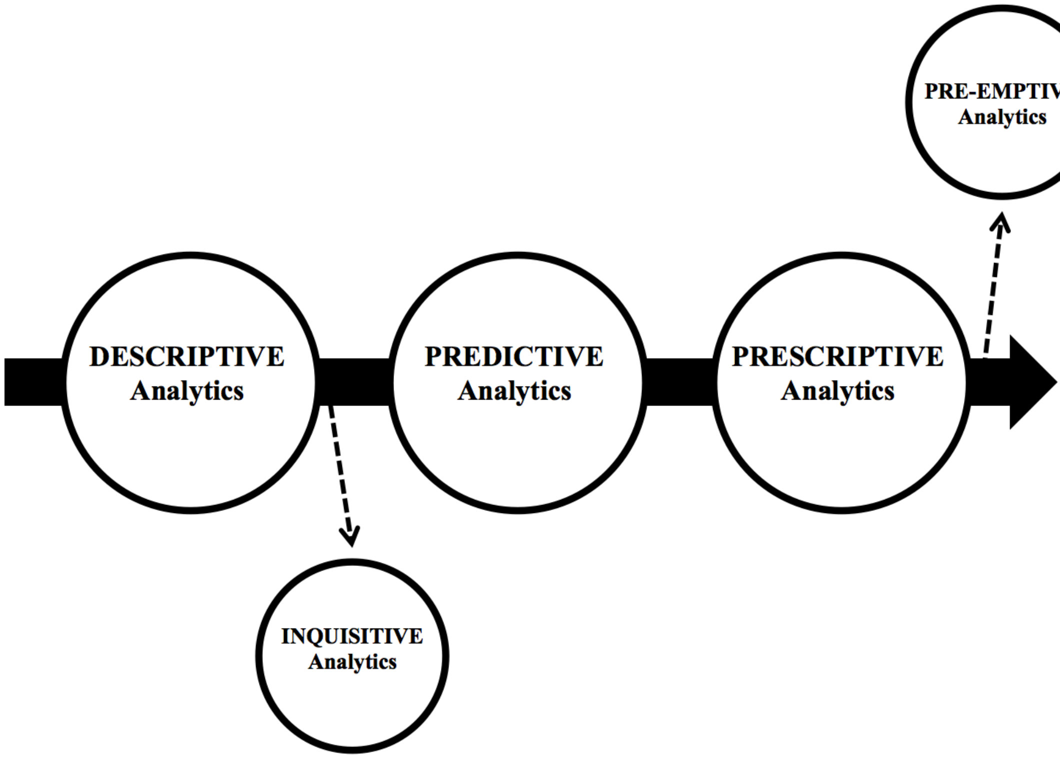

Figure 3. The levels of HR analytics (Adapted from Sivarajah et al. 2017.)

In addition to the three, already presented, levels of analytics, Mishra et al. (2016) present two complementary levels: *inquisitive* and *pre-emptive analytics*. The level of inquisitive analytics comes after descriptive analytics and refers to the examination of data in order to approve or reject business propositions. Examples of inquisitive analytics are, among others, analytical data drilldown and statistical analysis. Pre-emptive analytics, in turn, takes place after prescriptive analytics and focuses on the capacity needed to take precautionary actions on issues that will possibly have an undesirable effect on organization's performance. (Mishra et al. 2016.)

Moreover, Bersin (2014) has developed his own model to view the levels of HR analytics. It is called "Talent analytics maturity model" and it has four distinct levels: *operational reporting, proactive–advanced reporting, strategic analytics*, and *predictive analytics*. Organizations belonging to the first level focus only on operational ad hoc reporting that reacts to business demands. Data isolation and difficulty of analysis are characteristics for that organization group. Proactive–advanced reporting, in turn, refers to the state of analytics where operational reporting is used for benchmarking and decision making. Good examples are dashboards and multidimensional analysis. Third level is "strategic analytics" and it concentrates on segmentation, statistical analysis, and development of people models. The goal is to understand the cause and delivery of actionable solutions through the analysis of dimensions. The final level is labeled "predictive analytics" and on that level firms are developing and executing predictable models, scenario planning, as well as risk analysis and mitigation. On predictive analytics level, organizations have already managed, to some extent, integrate HR analytics to the overall strategic planning. (Bersin 2014; Isson & Harriot 2016.)

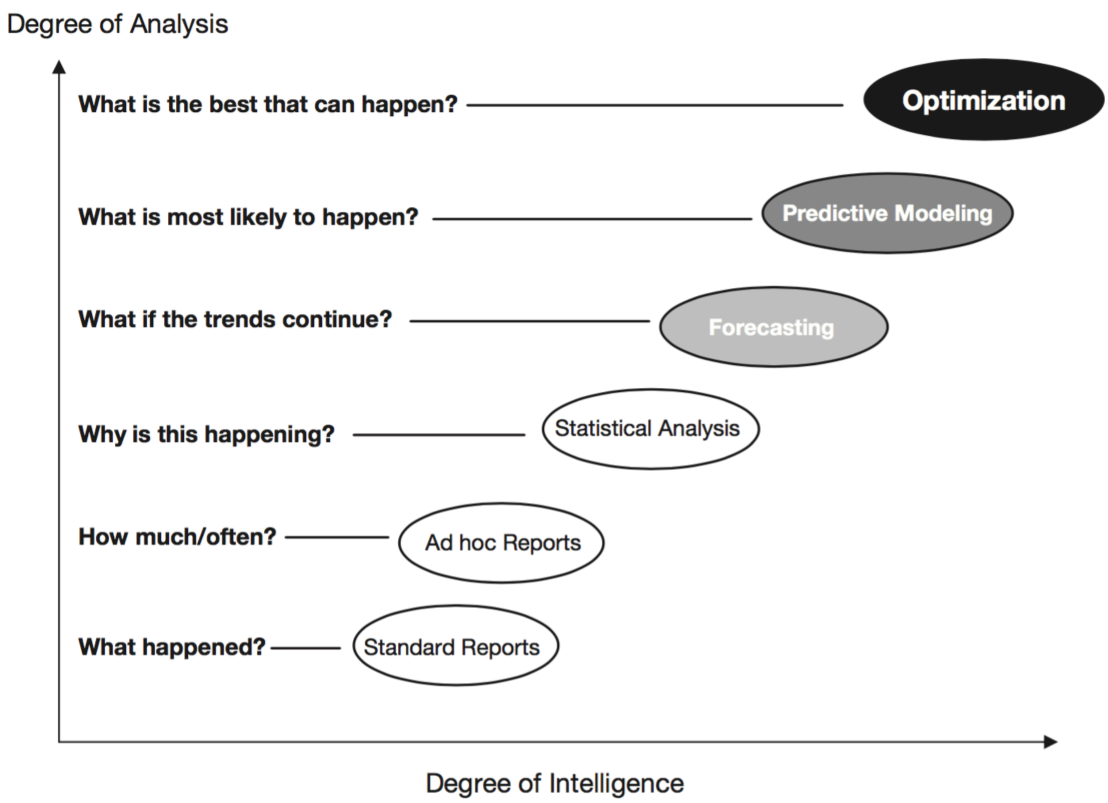

Figure 4. Degrees of analysis and business intelligence (Fitz-enz 2010: 186)

Like already mentioned, many organizations are still executing analytics on a very basic level in forms of basic operational (descriptive) metrics and reports (e.g. Boudreau & Cascio 2017; Minbaeva 2017). Unfortunately, data and metrics by them selves are not enough to help managers to make effective decisions (Fitz-enz 2010: 186). In fact, it can be even frustrating and confusing for managers to receive loads of reports and documents without any real insights (Fitz-enz & Mattox 2014). Therefore, it is crucial for organizations to progress on analytics levels to statistical analysis and eventually to predictions and optimization. By increasing the degree of analysis, organizations are also building up their business intelligence. (Fitz-enz 2010.) (See **Figure 4.**)

Fitz-enz (2010) describes the basic reporting as looking to the rearview mirror; it is limited to shed light into the things happened in the past. If an organization wants to understand outcomes and predict possibilities and events, more advanced analytics must be applied. The pressure and need to adopt HR analytics can also stem from external sources. Business is nowadays highly global and competitive, and in order to survive in an environment like that, forecasting, predictability, and advanced modeling become helpful. (Fitz-enz 2010.) But moving up from one level of analytics to another is not an easy or simple task or otherwise more companies would have adopted HR analytics. In fact, according to a survey conducted by Deloitte (2019), only 26 percent of respondent organizations report using HR analytics effectively.

A research conducted by Deloitte (2017a) suggests that the focus has, as a matter of fact, shifted from the already presented more "technical" stages of maturity to organizational enablement, culture, and skills development. Therefore it is insightful to present one more model concentrating on the organizational maturity when it comes to HR analytics. This model does not ignore the technical maturity but rather recognizes the fact that companies are still progressing it alongside with organizational maturity. The four levels in this model are labeled as *fragmented & unsupported, consolidating & building, accessible & utilized*, and *institutionalized & business-integrated* and they are supposed to be additive from one level to the next one. (Deloitte 2017a.)

The first level (Fragmented & Unsupported) refers to organizations that haven't really realized the value of data and its role as a core asset in gaining competitive advantage. The fact that data is not been treated as a value driver suggests two things. Firstly, companies are lacking data governance, which in turn undermines the value of data and makes the use of it unreliable and risky. Secondly, these kinds of firms have a culture where hierarchy, precedence, experience, and intuition overrun data in decision making.

As well as most other companies, also fragmented and unsupported organizations collect employee data through e.g. HR systems and surveys. However, these data collecting practices are often reactive and compliance-oriented in nature. Instead of having a dedicated HR analytics team, level 1 organizations have only distinct roles concentrating on HR analytics. These people are working in silos and mainly focus on basic reporting per requests. Approximately 14% of organizations are on the first stage of HR analytics maturity. (Deloitte 2017a.)

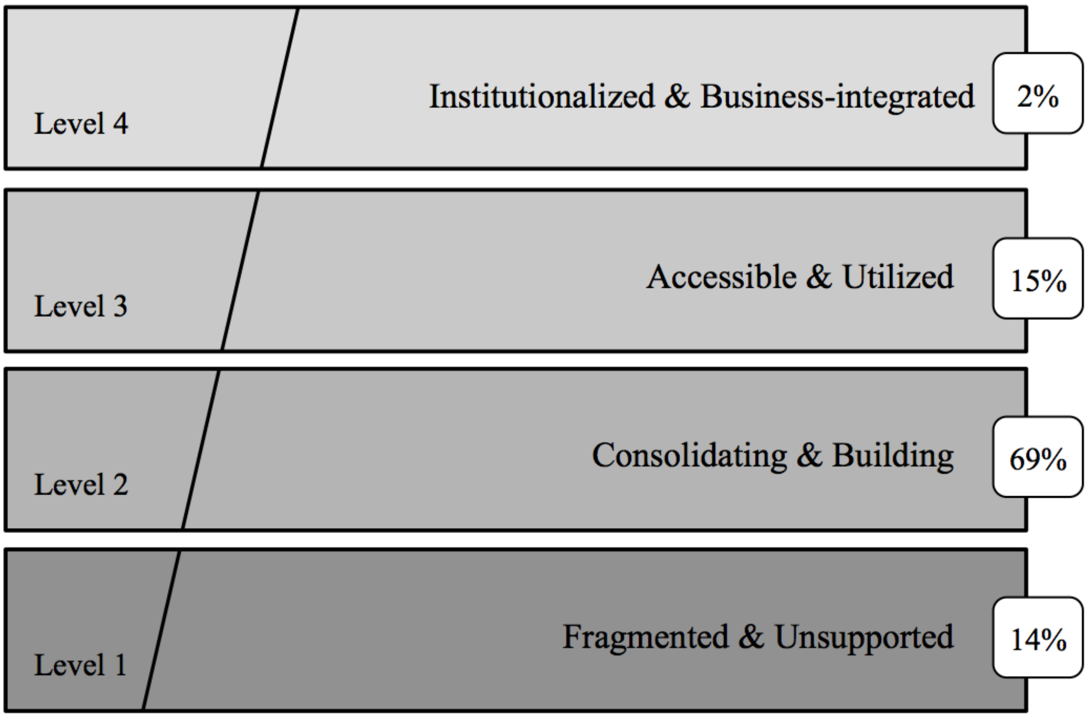

Figure 5. Maturity levels of HR analytics (Adapted from Deloitte 2017a.)

Today most of the organizations are located on the second level of HR analytics maturity as approximately 69% of organizations identify themselves as consolidating and building. These organizations have understood that gathering, tracking, and analyzing workforce data is valuable and therefore intuition, precedence, and former experience have started to loose their power in decision making to data and metrics. As data is understood as the core component of analytics, Level 2 organizations are investing in data consolidation, accuracy, timeliness, privacy, and security. The gradual goal is to have consistent data definitions in use in the whole organization for the most important HR metrics. The amount of sources, from which workforce related data is gathered, is more or less the same than on the first level. However, data is collected much more intentionally and promptly. At this level, organizations also strive to form a central HR analytics group by hiring and bringing together HR analytics oriented professionals from across the organization. (Deloitte 2017a.)

The third level of analytical maturity is labeled as "Accessible & Utilized". On that level organizations concentrate on ensuring that a considerably broader audience has the access to data and insights via automated dashboards, shared services, etc. That is possible due to the efforts made on the level 2. Because of the broadening audience, data and insights become more often used and embedded in key decisions concerning people and talent. Little by little they start to be present in regular work and everyday decision making. Also new tools, models, and approaches are experimented to study employee behavior. All of these aspects cause the need to educate the broader HR population further in basic data literacy skills, where to find what data, and how to use it. Moreover, one significant difference between the levels 2 and 3 is the mindset. On the third analytical maturity level the mindset has shifted from HR measuring HR to the already discussed outside/inside approach (Ulrich & Dulebohn 2015). Summarized, it can be stated that organizations on level 3 see considerable increase in investments relating to, for example, bigger analytics teams, more advanced analytics tools and technology, and third-party partnerships. About 15% of organizations have managed to reach this level of maturity. (Deloitte 2017a.)

The fourth and final maturity stage is labeled as "Institutionalized & Business-integrated" and only 2% of organizations have conquered this level. On this level HR analytics is seen as a part of organizational DNA as it is used throughout the company in people and business related decisions. In other words, HR analytics is elemental in working and decision-making. Also the data literacy in the HR function is on a considerably high level. Level 4 organizations have a wide collection of tools and technology in use. With the help of e.g. AI-aided, cognitive, and robotic process automation tools it is possible to quicker gather and analyze larger volumes of data, both structured and unstructured, from multiple different sources and use statistical methods. This leads to insights that are more progressive, accurate, and timely and these insights in turn are innovatively used to make the organization a better place to work. Instead of expanding the core HR analytics team in number, the team pursues to connect with different parts of business and diversify its skills and capabilities. Therefore, it is likely that the boundaries of the team become blurry and undefined. In other words, and also like Rasmussen & Ulrich (2015) state, HR analytics team may transform into "a cross-functional team that is responsible for data-driven decision-making across the organization in all people- and business-related matters". (Deloitte 2017a.)

In order to better understand what is needed to succeed in HR analytics and to move from the lower levels of analytics to the more mature and predictive analytics, the topic should be examined in sections. In fact, Isson & Harriott (2016: 53) claim that in order to gain excellence in HR analytics, prudent investments are required in people, processes, and technology. In addition to these three dimensions, also data and governance are regarded as analytical capability enablers (Deloitte 2011). Therefore, next in this paper all of these five interrelated dimensions are examined and discussed separately.

2.2.3. The people behind HR analytics

The overall shortage of data scientists is prevalent especially in HR. A solution to that, in addition to using the already existing analytics resources, tools, and technologies, is to build a team or a function of analytics consisting of people with various backgrounds. (Isson & Harriot 2016.) According to Fitz-enz & Mattox (2014), it is important that the analytic team fits with the organizational culture and structure and is positioned in a way that enables the hiring, training, growing, and retaining of the needed talent. Positioning and structuring can be done in many different ways, but it is always crucial to keep in mind the vision, brand, and culture of the organization. Analytic function can be centralized, decentralized, or some kind of variation between these two alternatives. However, before concentrating on the structure, it is important to focus on the people and activities. Without the right and suitable people, structure is indifferent. (Fitz-enz & Mattox 2014: 36.)

Fitz-enz & Mattox (2014: 36-37) note that the priority is to find the people who have statistical skills but also the enthusiasm and intuitive skills to go beyond analysis. The variety in backgrounds also enables the team to view data from different viewpoints and eventually to derive even more remarkable insight from it (Isson & Harriot 2016). McIver et al. (2018) have identified four central capability areas in HR analytics: *math and statistics*, *programming and database skills*, *domain knowledge including HR expertise and behavioral science*, and *communication and visualization*. As it is almost impossible to find an individual possessing all of these skills and competencies, also McIver et al. (2018) urge to form HR analytics teams. Isson & Harriot (2016) agree with the aforementioned skills and give examples of positions a skill-diverse analytic team might include. First off, they mention technical specialists who are responsible for working closely with IT teams to make sure "the collaboration and support needed to gather data from multiple sources and integrate, standardize, and govern it" works. (Isson & Harriot 2016.)

HR analytics teams need also statisticians, data scientists, and business intelligence specialist who help organizations to gain deeper knowledge about their talent life cycles and to better understand what is going on and why. These individuals are skillful in numerical analyses and capable of offering different views on challenges and the ways to overcome them. Moreover, they are able to use predictive models in order to prepare for workforce planning needs. These needs are among others the identification of talents the organization is at risk of losing and the candidates most likely to be successful once hired. Last, but not least, Isson & Harriot (2016) identify business analysts and navigators as essential actors in analytic teams. This group of people can be seen as the contact between the HR analytic team and the rest of the business. That is because they are the ones who paint the pictures of possible better futures that play a huge role in winning the C-suite over. (Isson & Harriot 2016.)

McIver et al. (2018) state that organizations usually need to look outside HR when building the HR analytic team with necessary skills. The fact is that most people in the HR position do not understand big data or analytics (Angrave et al. 2016). Ulrich & Dulebohn (2015) even state that many HR professionals chose the field of HR in order to avoid working with numbers. Therefore, individuals with the desired capabilities could be found from elsewhere, like IT and finance departments. Borrowing or buying capabilities from the external market is also a possibility. (McIver et al. 2018.) Rasmussen & Ulrich (2015) take the discussion even further and drastically state that HR analytics should be taken out of HR. They base their statement on the idea that when HR analytics mature, it first starts to collaborate more with other functions and departments and eventually end up looking at human capital elements in the whole value chain. In other words, it becomes a part of cross-functional analytics. (Rasmussen & Ulrich 2015.)

Through analytics it is possible to yield truly new insights only if several distinct fields and perspectives are combined together. Therefore, HR analytics must go beyond HR issues and join the bigger cross-functional business analytics. Rasmussen & Ulrich (2015) claim that adding a denomination in front of the word "analytics" indicates immaturity and unpreparedness to be part of the larger concept of analytics. According to them, HR analytics generally needs a couple more years to mature within the HR function before being ready to give away the prefix. This process can be sped up through "importing business analytics talent to run HR analytics". In fact, in most cases it is easier to teach analytics professionals HR than to shape HR professionals into statistics and analytics experts. (Rasmussen & Ulrich 2015.) Bassi (2011) disagrees with the aforementioned ideas as she says that no other function than HR should take the lead in HR analytics. Instead, HR should develop its capabilities and capacities to answer the new business requirement. (Bassi 2011.)

When it comes to constructing strong HR analytics capabilities, organizations normally tend to concentrate only on strengthening and developing the skills of the core analytics team. Even though that is a crucial aim, the skills among rest of the HR population should not be forgotten. It is equally important to enhance the data-literacy skills of analytics end-users. (Deloitte 2017a.) Sometimes the responsibility for educating and raising the level of analytical awareness within the HR function falls upon the analytics team itself (Boudreau & Ramstad 2004). Data literacy skills refer to simple data fluency, meaning the familiarity with basic statistical concepts, comprehension of the difference between correlation and causation or practical and statistical importance, ability to slice and dice data based on uncomplicated parameters, and understanding of appropriate data sources and formats. It is central to understand that the goal is not to have all HR professionals able to perform complicated analytical tasks. Instead, the idea is to increase the level analytical mind-set and data literacy. (Delotte 2017.)

There are multiple reasons why it is so important to be able to think analytically. First of all, when a people related problem arises, data literacy makes HR professionals more likely to ask the right questions. Moreover, being skillful in data literacy helps to better understand the problem at hand, instead of just jumping straight to the "solution mode", which is very typical for HR. Lastly, HR professionals with a basic understanding of analytics are better equipped to distribute insights, created by the core HR analytics team, to the rest of the business. (Deloitte 2017a.) According Subramanian (2017), organizations today are far from the desired level when it comes to analytical abilities. He says that analytical abilities must be strengthened throughout organizations, but HR function requires extra attention. These analytical capabilities can be increased by hiring, but as there is a prevailing shortage of qualified data scientists with human capital knowledge (Subramanian 2017; Kryscynski, Reeves, Stice-Lusvardi, Ulrich, Russell 2018) in the market, a better and more effective option would be to train existing staff. (Subramanian 2017.)

A study conducted by Deloitte (2017a) suggests that the size of an analytics team does not differ significantly between mature and immature organizations. Analytically mature organizations have approximately 6-10 members in their core analytics team while in immature companies the number is 1-5. However, other correlating factors can be identified. Instead of the size of the analytics team, there are three crucial elements that link with improved maturity. The first one is a team structure that enables strong connections with the business. It is important that teams have dedicated roles and responsibilities in order to "investigate the analytics needs of the business, communicate those needs to the core analytics team, and provide intelligence from that team back to the business". Secondly, as already discussed, teams must have a diverse set of competencies, skills, and expertise. Finally, what differentiates mature teams is that they report directly to the Chief Human Resource Officer (CHRO). (Deloitte 2017a.)

2.2.4. The processes of HR analytics

The second key factor in creating high-impact analytics is the processes (Isson & Harriot 2016). According to Fitz-enz & Mattox (2014), analytics is all about understanding the interrelationships and interdependencies of different parts of a process. Processes consist of inputs, throughputs, and outputs and by understanding the correlations between them it is possible to intervene to the two aforementioned to improve the outputs. (Fitz-enz & Mattox 2014: 50-52.) It can be argued that sometimes organizations tend to focus too much on the data. Data alone is not enough to bring value to an organization – actionable insights are also needed. For that, Isson & Harriot (2016) have developed the IMPACT cycle. (See **Figure 6.)** IMPACT cycle is to "guide analysts through the process of ensuring they are insightful business partners, rather than just purveyors of data". (Isson & Harriot 2016.)

Before presenting the different stages in an analytics process, it is necessary to discuss the needed building blocks behind it. McIver et al. (2018) state that an agile HR analytics process is built upon a foundation of three crucial components: *workforce analytics capability, workforce analytics vision*, and *strategic HRM perspective*. The first building block, the people and their analytical capabilities, is already discussed in this paper but the other two blocks still require examination. Workforce analytics vision provides two important aspects. First, it acts as a compass setting the direction and focus for the people behind the HR analytics. Secondly, it creates transparency by communicating the goals of HR analytics for the whole organization. In other words, vision shows the directions and helps the whole organization to understand what the people behind HR analytics are striving to do. Communication around the vision emphasizes themes like data-driven insights and expected performance benefits. (McIver et al. 2018.) In the long run, this kind of open communicating arguably leads to the development of data-driven decision-making culture. In fact, it has been claimed that "organizations can only reach their full potential in analytics maturity when data-driven decision-making is embedded in the culture". (Deloitte 2017a.)

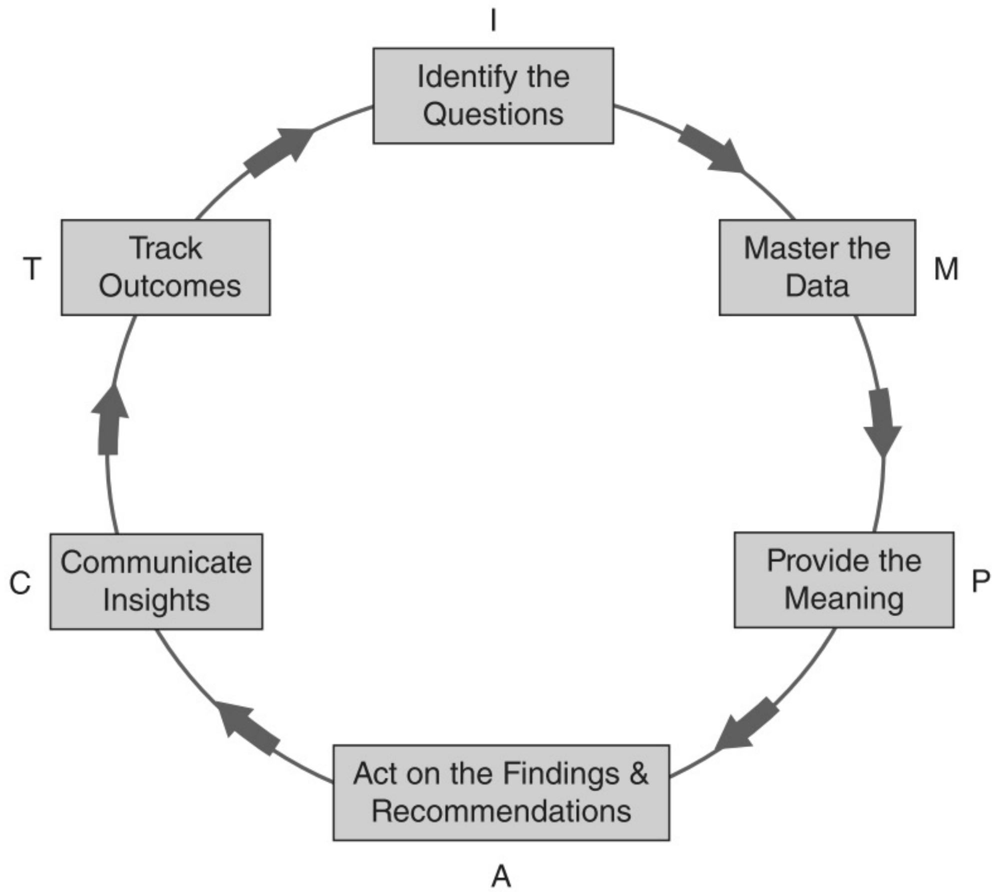

Figure 6. The IMPACT Cycle (Isson & Harriot 2016: 56.)

Strategic HRM perspective is the third required building block behind successful analytics processes. A strategic HRM framework or roadmap is a necessity if an organization desires to fully benefit from the potential of HR analytics. That is because these kinds or frameworks and roadmaps focus the attention on important outcomes and elements behind these results. They outline the central variables in a way that gives suggestions about their linkages that could be examined through HR analytics. Strategic HRM frameworks are also very useful for the people and teams behind HR analytics as they guide them in building long-term strategic capability as well as to continuously make operational improvements. Moreover, these kinds of roadmaps lay out a more comprehensive picture of the direction and offer a way “to create user buy-in through more short-term immediate impact projects”. (McIver et al. 2018.) A study conducted by Deloitte (2017a) agrees by claiming that strategic alignment with the business is key in analytical maturing.

Once these three building blocks are in order, organizations have better chances to be successful in their HR analytics processes (McIver et al. 2018). An organized process consists of all the steps needed to provide answers (Fitz-enz & Mattox 2014). The first step is naturally to identify the critical business questions that need to be answered (Isson & Harriot 2016). Like already noted, it is important for organizations to be able to ask the right questions (e.g. Rasmussen & Ulrich 2015; Simsek et al. 2019). While forming these questions, HR function must have an outside/inside approach that connects them with the broader business context (Ulrich & Dulebohn 2015). Second step is mastering data and it refers to the assembly, analysis, and synthesis of the available information. While conducting these actions, analytics team must keep in mind the already set questions. (Isson & Harriot 2016.) Like already said, HR analytics team must include people with wide range of background and skills (e.g. McIver et al. 2018) in order to produce simple, clear, and comprehensible visual presentations from the data available. These presentations are in forms of charts, graphs, tables, interactive data environments etc. (Isson & Harriot 2016.)

Third step in the process is labeled as “Provide the meaning”. After producing visual presentations, analytics team must articulate clear and succinct interpretations of the data and visuals. Once again this is done in the context of the critical business questions formed at the beginning of the process. (Isson & Harriot 2016.) Analytics for the sake of analytics is the wrong approach. Instead of just validating existing knowledge in practice, HR should try to add value to business decisions. (Rasmussen & Ulrich 2015.) The next step is to provide actionable recommendations based on the interpretations (Isson & Harriot 2016). Also Kryscynski et al. (2018) identify the importance of being able to translate results into understandable and actionable insights. As it is easier to react to a suggestion than to create one, it does not matter if they are off base. Furthermore, whenever possible, add a rough monetary figure “to any revenue improvements or cost savings associated with your recommendations”. (Isson & Harriot 2016.)

Fifth step is communication. According to Barrette (2015), as much as 45% of analytics team’s focus should be on communication. Also LaValle et al (2011) have identified the importance of communication in turning insights into value. Analytics team should have a multipronged communication strategy that guarantees insights to flow as far and as wide as possible in the organization. Communication can have several different forms like an interactive tool or an executive memo. Lastly, it is time to track outcomes. Analytics team should establish a way to follow the impacts of their insights. Future follow-ups with business partners are especially important. That way analytics team can keep track on what has been done, what were the impacts, and have new critical questions possibly risen during the process. (Isson & Harriot 2016.)

2.2.5. Technology in HR analytics

Marler & Boudreau (2017) define HR analytics as: “a HR practice enabled by information technology that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organizational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making”. Therefore, it can be argued that technology plays a big part in becoming analytically mature. As a matter of fact, it has been researched that strong analytics teams concentrate on actionable and scalable information delivery solutions. It is crucial to be able to deliver the insights to a wider audience, to every decision, and more frequently. In low maturity organizations this tends to be on the shoulders of the analytics team. Worst-case scenario is an organization without a team of analytics where the responsibility falls on a single individual. (Deloitte 2017a.)

Nowadays, the HR function is using cloud-based technology, software as a service (SaaS), and client-server solutions, while few decades ago they were still dependent on mainframe computers and manual payroll systems. The emergence of talent management systems has made it possible for organizations to gather, store, and manage a wide assortment of employee and HR data. While the amount of data increases, more and more technology companies with solutions to master the data appear on the market. (Isson & Harriot 2016.) Jones (2015) agrees, as she says that the amount of HR and talent applications and standalone analytics solutions have increased quickly. According to her, today those solutions and products that do not advertise the readiness for analytics are scarce. Instead, solutions include reporting tools, which are in most cases incorporated into human resources information system (HRIS) and talent management applications. (Jones 2015.)

HRIS and talent management software brings together data from a wide range of already existing HR-related databases into a single cloud-based data warehouse. Through HRIS software packages it is possible to e.g. assist career planning, manage performance and learning enrollments, as well as share knowledge in a user-friendly way. The main purpose of HRIS is to enhance HR processes and operations by making it more effortless and faster to access and comprehend key HR and employee data. In addition to these usual features, “all the major integrated talent management suites also include analytics modules”. They are displayed as a key advantage compared to the older HRISs. (Angrave et al. 2016.)

However, there are still deficiencies when it comes to HRISs. As already stated in this paper, HR analytics literature emphasizes that HR data is mainly realized by using it to answer critical strategic questions about how people create value for the company, so that value can be apprehended and exploited (e.g. Rasmussen & Ulrich 2015; Angrave et al. 2016). “The analytics modules of HRIS software packages as they are typically sold and implemented do not have the capacity to perform this sort of analysis.” Even the big multinational corporations (MNCs) that have spent enormous amounts of money and resources in HR analytics and have achieved results in analytics in other areas of business admit that their HR analytics programs are stuck in reporting historical information only. In other words, many organizations have failed to develop forward-looking strategic analysis with very little ideas how to implement big data into their HR analytics programs. (Angrave et al. 2016.)

According to Bersin (2015), the reason why existing talent management software is already outdated is the fact that it was designed to bring solutions to the problems of the last decade. Nowadays, instead of the “war for talent”, organizations are facing challenges relating to engagement, empowerment, and environment. Seeing people entirely as “talent” has become a narrow and limiting concept. Organizations naturally want to hire, train, develop, and lead people in order to gain results but it is important to see employees as individual people who have their own reasons and motives to come to work. Therefore, the focus should rather be on “people” than “talent”. (Bersin 2015.) Sommer (2015) gives a contrast to Bersin’s (2015) ideas as he claims that instead of HR technology, the problem is HR itself. According to him, HR departments are not ready for new technologies at the moment. That is because of the lack of awareness or skills in these technologies. Like already mentioned, HR function is missing the people with analytical competencies. (Sommer 2015; DiClaudio 2019.) Therefore, a rebalancing of talent within HR organizations is necessary. “New skills, capabilities and insights are needed to make HR more relevant and able to exploit today’s new HR technologies.” (Sommer 2015.)

Nevertheless, HR analytics can be seen as a journey and therefore it is wise to start small and first master the workforce information already at disposal. Also, it is good to leverage the experts in the field of traditional analytics technology as they can help organizations to map out the best and most suitable approaches. (Isson & Harriot 2016.) According to Berry (2015) many organizations tend to spend a lot of money in building their own technology infrastructures while, in fact, “rightly positioned and properly executed, partnerships with vendors will pay a multiplier several times greater than the return on investment in your own technology”. Truth is that today’s tech vendors are very service minded and want to help their clients to over come their challenges. By choosing to go with a vendor, HR analytics can also avoid being considered as a huge expense that can end up on chopping board when cutting costs. (Berry 2015.)

2.2.6. Data in HR analytics

Analytics can draw insights from both internal as well as external data sources (Deloitte 2011). Examples of data sources are among others HRIS, learning management systems (LMS), social media, surveys, and public data from outside the organization. For every data source, it is important to be aware, what the data is, where the data is housed (DiClaudio 2019.), who owns the data, how to collaborate with the owner, how to access and integrate the information with other data, and how valid and reliable the data is. (Pease et al. 2013.) However, like already referred, the technical ways to integrate, organize and analyze data stored in traditional HRIS with data from these larger unstructured sources are not yet fully established. Privacy, consent, and ethics are also issues that need to be considered when storing and analyzing HR and people data. (Angrave et al. 2016.)

Once you have a vision of what you need in order to create reports and conduct analysis, the next step is to determine where the critical data resides and who owns it. According to Fitz-enz & Mattox (2014: 74-75), in most cases it is IT that controls the data. That is because in the majority of organizations the tools, like LMS or HRIS, are implemented and maintained by IT. (Fitz-enz & Mattox 2014.) Due to the advancements across the technology industry, it is nowadays much easier to get a hold of information as various types of data are nowadays resident in one system. Before organizations started to invest in HRIS upgrades the data was held in separate pieces of software designed to perform different HR processes. (Fitz-enz & Mattox 2014; Angrave et al. 2016.) Another supporting factor is the fact that distinct systems today are often integrated under one single service provider. One good example is SAP, that acquired SuccessFactors, and is now the owner of a system that can report hiring information, training histories, compliance, performance appraisal scores, high potential status, promotion history, compensation and benefits information etc. However, there are still organizations that house their valuable HR data in multiple distinct systems. (Fitz-enz & Mattox 2014.)

After identifying the source of data, the next step is to know who has the ownership of the data. According to Fitz-enz & Mattox (2014), the owners are sometimes unable or unwilling to share the data. There is often an acceptable reason behind that. The reason can be, for example, that it is not possible to export data to a file from the system. Another, and a more common, reason is the sensitivity of data, which is due to government regulations or organizational policy. This kind of data includes personal information, such as gender, age, ethnicity, and medical history and is therefore protected. (Fitz-enz & Mattox 2014.) The developments in technology have offered considerable advantages in terms of data processing efficiency and productivity. However, at the same time these advancements cause worry about individual rights. There is discussion about whether these otherwise positive developments have an adverse effect on the privacy of individuals and that this would be aggravated when viewing in an international context. These concerns have led to measures like the enactment of the General Data Protection Regulation (GDPR). (Ustaran 2018.)

Besides privacy, the ownership of data is nowadays, in fact, a complicated issue. Due to the existence of, for example, social media, there are tons of real time data available. (Sivarajah et al. 2017.) Moreover, data can be gathered on e.g. what the employee does, who they communicate with, and what they communicate about. That kind of information resides in the location data from cell phones, internet browsing histories, electronic calendars, email, phone records, SMS messages etc. However, there are important issues of privacy, consent, and ethics to consider when housing and analyzing HR and people data. (Angrave et al. 2016.) With advances in privacy regulations, such as the already mentioned GDPR, HR analytics practitioners may have to re-think their approaches and procedures. Although lawyers, ethicists, and management scientist are already focusing on these issues, it still remains a blind spot for the HR analytics profession itself and therefore requires attention. (Tursunbayeva, Di Lauro & Pagliari 2018.) Alongside the issue of ownership, arise the questions about controlling and ensuring data accuracy. (Sivarajah et al. 2017.)

To any analysis it is essential to have quality data. Before engaging with analysis it is necessary to examine the data in order to be sure it contains the appropriate measures and that those measures are collected and stored consistently. (Fitz-enz & Mattox 2014: 80.) In fact, Andersen (2017) states that bad data is one of the biggest problems when considering the quality of HR analytics. According to him, low-quality HR data cost greatly for organizations. Therefore, in order to be able to guarantee better data quality and avoid additional costs, it is crucial to understand why bad data happens. The first reason is the lack of coherent data strategy. In other words, purely operational approach to data is not enough to ensure proper data quality. Another mistake is to assume that analytics software is the answer to the problem while in reality it is just another data collection tool. "To get the most out of HR analytics you must go through a strategic data process and decide what data are of strategic importance to you and how they ideally look like." Thirdly, it is crucial to acknowledge that the data are as good as the component inputs – "garbage in, garbage out". Finally, not having critical data sources affects the data quality. All in all, analysis and decision-making based on poor and low-quality data is meaningless. (Andersen 2017.)

2.2.7. Governance in HR analytics

In this paper the last identified factor to have an influence on HR analytics maturity is governance. It is important for organizations to identify how analytical decisions are made and who should be the accountable for facilitating the analysis and leveraging it insights. (Deloitte 2011.) According to Feinzig (2015), once the analytics objectives are established it is central to communicate expectations and define working relationships with stakeholders. Like already stated, HR professionals pursue to make sure that the work of HR function contributes positively to overall business outcomes. Therefore, it is necessary to cooperate with business leaders and HR business partners in order to single out the business challenges and opportunities that can be addressed through workforce related actions. Furthermore, the members of the analytics team have to have a proper understanding of the key metrics used in managing the business and their current levels. HR business partners are helpful in identifying, which HR related actions impact the business metrics. (Feinzig 2015.)

It is arguably possible to identify data governance from the more comprehensive concept of governance. According to Patre (2016), proper data governance ensures that people use analytics as it was intended. The lack of data governance not only undermines the value of data but also makes it risky to use in any shape or form (Deloitte 2017a). In an efficiently functioning analytics process, the data inputs have to be consistent and reliable in order for information outputs to be relevant and comparable. When describing computing information, the four desired adjectives are relevant, reliable, comparable, and consistent. Effective governance implies that data used in decision-making is of consistent quality and from trustworthy sources. Moreover, when being efficient, "governance leverages connectivity and technology to enable the comparison of data from many different sources and to deliver relevant analysis." (Smith & Heffernan 2019.)

The data governance problems can be divided into two camps. First of all data governance can be ineffective, which means that the data quality is insufficient to be used in decision-making. Inefficient data governance, in turn, refers to data that cannot be accessed. All of the governance issues cause people not to trust the data and the decisions made based on it. Usually the mistrust is due to ineffective governance. It is possible that organizations are unaware of critical governance tools or have gap in communication between the data owners and the end users. Ineffective governance is normally easier to resolve, as inefficiency is sometimes needed due to regulations, like the already mentioned GDPR. (Smith & Heffernan 2019.) Feinzig (2015) emphasizes that it is crucial to understand data privacy legislations in each country where data is being gathered and analyzed. According to her, these laws and rules must be followed at all times. (Feinzig 2015.) Analytically mature organizations tend to ensure effective and efficient governance by establishing an organization wide data council or making sure the already existing data council has enough HR representatives. According to study conducted by Deloitte (2017a), data councils normally consist of couple of individuals from each business unit and corporate function. (Deloitte 2017a.)

2.2.8. Theoretical framework of the study

This paper investigates the factors affecting HR analytics maturity. The aim is to figure out the current status of HR analytics in the case company as well as to identify the hindering factors in its development process. According to the already existing literature, there are arguably five main topic areas that are central in HR analytics: *people, processes, technology, data*, and *governance*. Furthermore, within these topics it is possible to identify more specific hindering factors. All of these together form the following theoretical framework of the study.

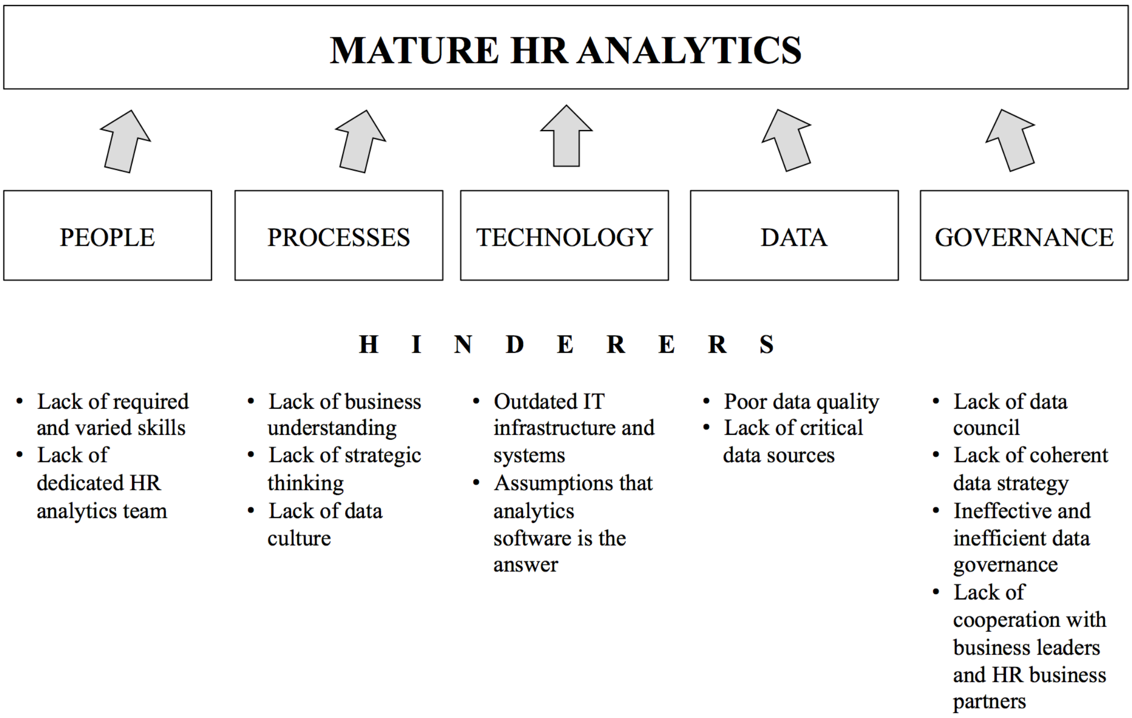

Figure 7. Theoretical framework of the study

3. METHODOLOGY

In this part of the paper the specific procedures and techniques used to identify, select, process, and analyze information about the topic are presented. In other words, the aim is to answer how the data was collected and analyzed. Furthermore, based on the section the reader should be able to critically evaluate the study's overall validity and reliability.

3.1. Research approach

According to Creswell (2014: 3), research approaches can be defined as "plans and the procedures for research that span the steps from broad assumptions to detailed methods of data collection, analysis, and interpretation". He identifies three different kinds of approaches: qualitative, quantitative, and mix methods. Qualitative research is seen as an approach to explore and understand the meanings individuals or groups attribute to a social or human problem. It is typical for qualitative research process to involve merging questions and procedures, data that is gathered in the participant's environment, inductively building data analysis, and interpretations of the meaning of the data made by the researcher. Quantitative research, in turn, is more about testing objective theories by studying the relationships between different variables. These variables are normally measured on instruments in order to get numbered data to analyze through statistical procedures. Finally, the mix methods research approach can be defined as an inquiry including both quantitative and qualitative data. The main ideology behind this approach is that "the combination of qualitative and quantitative approaches provides a more complete understanding of a research problem than either approach alone". (Creswell 2014: 3-4.)

Throughout history, quantitative research has been the more popular option in business research (Creswell 2014: 4; Eriksson & Kovalainen 2016: 4) and qualitative research has been described mainly by comparing it with the aforementioned. However, both approaches have a great deal of internal variety, which makes candid comparison between the two inadequate. (Eriksson & Kovalainen 2016: 4.) Creswell (2014: 3) agrees as he says that qualitative and quantitative approaches should not be seen as distinct opposites but rather as different ends of a continuum. Still, it can be argued that one of the most notable distinctions separating these two approaches is the fact that qualitative research is about interpretation and understanding while quantitative research is concerned with explaining, testing, and making hypotheses (Eriksson & Kovalainen 2016: 4).

Moreover, it can be generalized that "in qualitative research approaches, the collection of data and their analysis are sensitive to the social and cultural context aiming at a holistic understanding of the issues studied". Quantitative research, for one's part, is more devoted to structured, standardized, and abstracted ways of gathering and analyzing empirical data. (Eriksson & Kovalainen 2016: 4.) As this thesis aims to thoroughly understand the current state of HR analytics and identify the pivotal factors in its maturity development in the case company through interpreting the experiences, attitudes, and perceptions of the company's representatives, the qualitative research approach is justified.

3.2. Philosophical assumptions

Research approach involves also philosophical assumptions. Although these philosophical ideas tend to stay hidden in research, they still have an influence on the practice and therefore need to be identified. (Creswell 2014: 5-6.) The philosophical framework of research consists of multiple areas, one of the most important ones being *ontology*. Ontology asks questions about the nature of reality. Moreover, it is about how the research subject is understood on a deeper level. (Hirsjärvi, Remes & Sajavaara 2007: 125-126.) The division between objectivism and subjectivism is a central aspect of ontology in philosophy. Objectivism expects the social world to exist separate from the people and their actions and activities, while subjectivism (i.e. constructionism) presumes that "social actors produce social reality through social interaction". (Eriksson & Kovalainen 2016: 14-15.) According to Hirsjärvi & Hurme 2001: 22), quantitative research approach tends to see the reality as objective and congruent, whereas in qualitative approach it is often seen as subjective and manifold, depending on individual experiences. While keeping in mind the purpose and aim of this study, it can be stated that the thesis is based on constructionism.

Ontology is strongly linked to epistemology. Therefore, they are often discussed together. While ontology is concerned about what the world contains, epistemology wonders questions like "What is knowledge" and "What are the sources and limits of knowledge?" (Eriksson & Kovalainen 2016: 15.) In other words, epistemology of the research refers to the origin and nature of knowledge and the relationship between researcher and subject (Hirsjärvi et al. 2007: 126). Epistemology too can be divided into objectivist and subjectivist views. Objective view believes to the existence of a world that is external and theory neutral, while subjective epistemological view considers the world beyond our own interpretations and observations inaccessible. (Eriksson & Kovalainen 2016: 15.) As the qualitative research approach underlines the importance of constant interaction between the researcher and the subjects (Hirsjärvi & Hurme 2001: 23), researcher can be seen as part of the knowledge production process (Eriksson & Kovalainen 2016: 16). In other words, qualitative research tends to take the subjective epistemological view where the researcher takes a participatory role.

According to Eriksson & Kovalainen (2016: 16), epistemological views and thoughts are associated with the different philosophical positions, including positivism, interpretivism, and critical realism. Positivism leans to an assumption that only valid knowledge can be found from experience. It links to the epistemological view of empiricism, "in which the reality is constituted of observable material things". Interpretivism, in turn, is interested in how individuals and groups interpret and understand social occurrences and settings. Interpretivism is associated with subjectivism, which sees reality as socially constructed. Finally, critical realism combines ideas from both positivism and interpretivism. This philosophical position believes that there is an observable world, separate from human consciousness, while also suggesting at the same time that the knowledge of the world is socially constructed. From the epistemological views, substantialism is associated with critical realism.

According to substantialism, reality is material that people interpret differently depending on time and context. (Eriksson & Kovalainen 2016: 16-20.) The base for this study is interpretivism, as the knowledge is gained through interaction and shared meanings between the researcher and subjects.

Lastly, in order to also understand how the scientific knowledge is achieved it is justifiable to discuss the reasoning logic. Reasoning logic can be described to be either inductive or deductive (Tuomi & Sarajärvi 2009: 95). Inductive research starts from empirical findings and thereafter proceeds towards theoretical results, while deductive approach starts with theory and hypotheses construction. According to Eriksson & Kovalainen 2016: 23), most research in the field involve both inductive and deductive reasoning processes. In those cases the study logic can be described as abductive. In this thesis the research process starts with comprehensive literature review and theory, which is later on tested through empiricism. The aim is to reevaluate the already existing theories and contribute to the research by empirical findings. According to abduction logic, theory formation is possible when observations are made based on some kind of thread or clue (Tuomi & Sarajärvi 2009: 95). Therefore, the research logic in this paper is arguably abductive in nature.

3.3. Research strategy

The concept of research strategy refers to the ensemble of methodological solutions used in a study. The purpose of the study as well as the research problem affects the decisions on research strategy. According to Hirsjärvi et al. (2007: 130), there exist three traditional research strategies: *experimental studies, surveys*, and *case studies*. An experimental study examines the effect of one variable to another and it is typically executed in a controlled environment where it is possible to make intended and systematic changes in conditions. Measuring is normally numerical. Surveys, for one's part, are about gathering information about a group of people in a standardized form. The collection of material happens through questionnaires and structured interviews and the material is eventually used to describe, compare, and explain phenomena. Lastly, case study is used to acquire detailed and intensive information about a single case or small number of linked cases. Information is normally gathered by using multiple different methods, like observations and interviews. (Hirsjärvi et al. 2007: 128-131.)

From the categorization above, the most suitable research strategy for this thesis is the case study. Like the name suggests, in case studies the focus is normally on one or few observation units. Case study is chosen when information is wanted on special cases or the research problems are comprehensive, groundbreaking, or in-depth in nature. (Hirsjärvi & Hurme 2001: 58.) According to Eriksson & Kovalainen (2016: 131), case studies generate holistic and contextual in-depth knowledge by using many different data sources. In general, case study research pursues to take into account diversity and complexity and, thus, avoids too simple research designs. Despite the fact that case studies are qualitative in spirit, also quantitative data can be exploited. As a matter of fact, there is no limit on how much empirical data can be used in a case study research. Also, the ways in which the data is analyzed in case studies varies a lot due to the distinctive study aims. Therefore, case study research should arguably be seen as a research strategy, rather than just a method. (Eriksson & Kovalainen 2016: 132.)

There are several ways to do a case study research depending on factors such as the purpose of the study and the nature of the research design. However, in general case studies can be divided into two camps: *intensive* and *extensive* case study research. "Intensive case study research aims at understanding the case from the inside by providing a thick, holistic and contextualized description and interpretation." Extensive case study research, in turn, tries to advance or generate theory through the comparison of number of cases in order to achieve generalization. (Eriksson & Kovalainen 2016: 133.) The aim of this thesis is to obtain a comprehensive understanding of the current state of HR analytics and the factors affecting its maturity in the target company. Therefore, it can be argued that the research strategy used in this thesis is an intensive case study.

The case company in question is a Finnish MNC operating in industrial goods and services –industry, quoted in the Nasdaq Helsinki. The organization has a complex structure with three distinct business areas. Overall, the company has over 12 500 employees globally and it operates in over 100 countries. To secure the anonymity of the case organization and its representatives, the company name or individuals' information are not mentioned in the analysis.

Number of employees	Number of countries where own employees	Number of operating countries
~ 12 500	~ 45	>100

Table 3. The characteristics of the case company at the end of 2019

3.4. Data collection

First of all, data can be divided into to two categories based on their source: *primary* and *secondary* data. In most cases the researcher collects his/hers own data. This kind of empirical material includes immediate information about the research subject and is therefore called as primary data. Secondary data, in turn, refers to material that is already collected by someone else. (Hirsjärvi et al. 2007: 181.) When deciding on data collection methods, criterion like efficiency, economy, accuracy, and reliability should act as a base and guide decision-making (Hirsjärvi & Hurme 2001: 34). The most common data collection methods in qualitative research are interviews, surveys, observation, and information from different documents. These can be used separately, side by side, or combined, depending on the research problem and resources available. (Tuomi & Sarajärvi 2009: 71.)

According to Eriksson & Kovalainen (2016: 138), in-depth interviews are commonly utilized as primary source of data in business research, more precisely in case studies. There are multiple reasons behind the selection of interviews as the data collection method, one of them being the urge to emphasize people as active research subjects creating meanings. Interviews are also most suitable for relatively unknown topics as they enable the unspecified direction of answers. Moreover, interviews also facilitate a wider context and make it possible to clarify and deepen the received answers and information. (Hirsjärvi et al. 2007: 200.) Eriksson & Kovalainen (2016: 81) further suggest that interviews allow the study of individual's perceptions and experiences. That is arguably because interviews are to some extent like discussions that include both verbal and non-verbal communication. That kind of interaction transmits also thoughts, attitudes, opinions, knowledge, and feelings. (Hirsjärvi & Hurme 2001: 42.) Hirsjärvi & Hurme (2001: 14) summarize it well by stating that interviews as the data collection method in research are flexible and suitable for many starting points and purposes.

An interview used for research purposes should be understood as a systematic data collection method. Interviews have goals and they aim to acquire as accurate, reliable, and valid information as possible. Therefore, it is actually more informative to use the term "research interview". Research interviews can be divided into many different categories. The most used way to make these allocations is arguably based on how structured and formal the interview situation is. (Hirsjärvi et al. 2007: 202-203; Hirsjärvi & Hurme 201: 43.) The selection of research interview titles is varied and sometimes even confusing (Hirsjärvi & Hurme 2001: 43). Among others, Hirsjärvi et al. (2007: 202-205) try to elucidate the matter by presenting three "main" groups for research interviews: *structured interview*, *theme interview (semi-structured)*, and *open interview (unstructured)*. Structured interview is executed by following a form, the content and assemble of the form being predetermined. The other extreme is an open interview, where the researcher is responsible for controlling the discussion. In other words, an unstructured interview does not follow a script but discussion is free-flowing. (Hirsjärvi & Hurme 2001: 44-46; Hirsjärvi et al. 2007: 203-204; Tuomi & Sarajärvi 2009: 74-77.)

This study employs semi-structured interviews that can be seen as the intermediate option between structured and open interviews. For theme interviews it is typical that question topics (themes) are known in advance, but the exact form and order of the questions is lacking. (Hirsjärvi & Hurme 2001: 47-48; Hirsjärvi et al. 2007: 203; Tuomi & Sarajärvi 2009: 75.) These predetermined themes are chosen based on the research framework and already existing theory (Tuomi & Sarajärvi 2009: 75). Based on all the facts presented above and the note that this thesis aims to, based on prior theory, understand the current state of the case company's HR analytics and identify the pivotal factors in its maturity development, the use of semi-structured interviews as data collection method is justified.

In qualitative research the goal is not to make generalizations but rather to describe a phenomenon, understand behavior, and give a theoretically meaningful interpretation for a certain occurrence. Therefore, instead of concentrating on the quantity of research material it is more important to make sure that the people from which the material is collected from have enough knowledge and experience on the topic and phenomenon. In other words, the selection of the interview participants should be cautious and purposeful. (Tuomi & Sarajärvi 2009: 85-86.) In total, seven individuals were selected for interviews. These respondents represent those who are responsible for and have the most experience with HR analytics in the case company. The interviews were built around six focal themes that guided the discussion. (See Appendix.) All interviews, except one, were conducted as individual, face-to-face, interviews. The first two participants were paired for the interview, as they are members of the same team. Interview details are presented more specifically in the following table. (See **Table 3**.)

Respondent	**Position of the Respondent**	**Duration of the interview**	**Language**
1	Talent & Leadership Development Consultant	00:52:48	Finnish
2	VP, Talent & Leadership Development		
3	VP, Performance & Rewards	00:58:43	Finnish
4	Compensation & Benefits Specialist	00:43:52	Finnish
5	VP, Human Resources	00:36:48	Finnish
6	Senior Manager, Compensation & Benefits	00:24:28	Finnish
7	SVP, Human Resources	00:39:28	Finnish

Table 4. Interview details

3.5. Data analysis

Once the empirical data is collected, the next step is to analyze, interpret, and draw conclusions. This phase can arguably be seen as the most vital part of the research. (Hirsjärvi et al. 2007: 216.) One basic method for analysis that can be used in all traditional qualitative studies is content analysis. In fact, it has been stated that most of the analysis methods used in qualitative research studies are more or less based on content analysis. (Tuomi & Sarajärvi 2009: 91.) Eriksson & Kovalainen (2016: 119-120) define qualitative content analysis as "the ways of analyzing the content and meaning of different types of qualitative data". This kind of analysis concentrates on the content of data with emphasis on the ways something is said and done. In addition, the prefix "qualitative" suggests that the aim is also to understand the contextual meanings of the data with the help of questions like "How something is said and done" and "Why in that particular way". (Eriksson & Kovalainen 2016: 119-120.)

The data used for qualitative content analysis can be in different forms, like transcribed interviews, written documents, video/audio recordings, and pictures etc. (Eriksson & Kovalainen 2016: 120). The interviews conducted for this thesis were recorded and saved as audio files. Once the data is recorded, the researcher has basically two alternatives to decipher the data. First option is to transcribe the data into text, entirely or partially. This means that instead of writing everything word for word, the researcher may decide to transcribe only, for example, the sayings of the participant or leave out the things that are not relevant considering the predetermined themes. The second alternative is to make conclusion directly from the recorded data. That is possible and manageable when there are only few interviewees and the interviews do not last long. (Hirsjärvi & Hurme 2001: 138; Hirsjärvi et al. 2007: 217.) In this study both approaches were exploited. In addition to transcribing the most important and central perceptions per theme into a written format, some conclusions were made straight from the interview recordings. That is due to a fairly tight schedule. Also, as the size of empirical data in theses is generally small (Tuomi & Sarajärvi 2009: 85), making immediate conclusions from the data is justified.

Hirsjärvi et al (2007: 218) claim that the processing and analysis of data should be commenced right after the data collection, while Saunders, Lewis & Tornhill (2009: 485) generalize that the analysis begins already simultaneously with the data gathering process and continues from there on. The data analysis practices can be divided into three groups: *data-driven analysis, theory-driven analysis*, and *theory-bonded analysis*. In data-driven analysis the aim is to create theoretical entity from the empirical data. In other words, prior observations, knowledge, or theories should be insignificant as analysis is expected to be data-driven. Theory-driven analysis, in turn, leans to an already existing theory or model. Ideally, the data is being analyzed according to a framework that is developed based on earlier information and knowledge on the topic. Lastly, the intermediate of these two aforementioned approaches is theory-bonded analysis. It can have theoretical linkages or theory can help to proceed with analysis process. The idea is not to test prior theories but theory, in a way, acts as a guide in exploring new ideas and viewpoints. When talking about the reasoning logic of theory-bonded analysis, it is often about abductive logic. As already reasoned, this thesis leans to abductive research logic, which for one's part supports the selection of theory-bonded analysis. (Tuomi & Sarajärvi 2009: 95-97.) Therefore, the data analysis in this thesis can be described as a qualitative, theory-bonded content analysis.

3.6. Reliability and validity of the study

When conducting a research, one aim is always to avoid errors and mistakes. Even so, the reliability and validity of results tend to vary among studies. That is the reason why every research pursues to evaluate the accuracy of conclusions through different measuring and examinations methods. (Hirsjärvi et al. 2007: 226; Tuomi & Sarajärvi 2009: 134.) Reliability refers to the repeatability of the research. In other words, reliability means the study's ability to give non-random results. Validity, in turn, considers the feasibility of research methods and instruments. That is to say, how well these chosen methods and instruments manage to measure what they are supposed to measure. (Hirsjärvi et al. 2007: 226.) Both concepts stem from the quantitative research (Hirsjärvi & Hurme 2001: 186; Hirsjrvi et al. 2007: 227) and therefore as such are not that suitable for qualitative research. As a matter of fact, researchers even tend to avoid the use of these concepts in qualitative studies. (Hirsjärvi et al. 2007: 227.)

Even if those aforementioned terms are avoided, the trustworthiness and competence of qualitative research should still somehow be evaluated. The reliability of a qualitative research can be improved by explaining in detail how the research was conducted. Each step in the study should be elaborated and the conditions for empirical data acquiring ought to be described clearly and truthfully. This includes, for example, describing the circumstances in which the data was collected, time spend on the interviews, and plausible disturbance factors. All in all, the progression of the research and the decisions concerning the study should be as accurate and transparent as possible to the reader. (Hirsjärvi et al. 2007: 227-228.) These aspects were acknowledged also in this thesis and therefore the decisions regarding the methodological choices, research strategy, as well as the empirical data collection and analysis are reasoned in detail.

One important factor to consider when conducting research in an international setting is the language used in interviews. According Welsh & Piekkari (2006), there are three valuable reasons why it would be good to communicate in the respondent's language: it enables interviewees to better express themselves; it institutes consensus; and allows "the interviewer to interpret the interviewee's statement with cultural understanding". Moreover, the selected language may also have power implications for the relationship between the researcher and the respondent. (Welsh & Piekkari 2006.) The interviews, conducted for this thesis, had the linguistic advantage as Finnish is the mother tongue of both the researcher and the interviewees. That is very profitable as the interviewees that are able to express themselves in their native tongue are more likely to produce authentic and valid answers (Welsh & Piekkari 2006).

4. FINDINGS AND DISCUSSION

In this section of the paper the findings from the analysis of the empirical data gathered through the interviews with the case company representatives are presented. Furthermore, these findings are contrasted and discussed with the findings and results from previous research, taking also into consideration the characteristics of the case company.

4.1. Views on HR analytics in the case company

> *”HR is definitely a strategic partner in our organization. Otherwise I would not be working here.”*

Like already discussed in this paper, HR is transforming from a lower level, administrative and maintenance oriented function into a strategic business partner that is seen as a core organizational operator (Ulrich & Dulebohn 2015). Based on the interviews, it can be argued that the case company representatives consider the HR function as a strategic partner. It was stated during the interviews that business driven HR is strongly emerging – not only in operative doing. Having the right people in right places is an important requirement for success. Moreover, well-planned and wisely structured workforce can be seen, according to the interviewees, as a competitive advantage that is very hard to copy. Yet, respondents admitted that HR is still often seen as a “soft” line of business and that there is a crying shortage of “hard” HR professionals. One of the interviewees described “hard” HR professionals as people who manage to create a people plan that enables the success of business strategy.

> *“[…] Strategy is implemented through people and if we manage to build the suitable management systems and acquire the right workforce then the success in strategy is enabled.”*

The view on HR as a strategic partner was also challenged during the interviews. It was stated that the concept of strategic partnership can always be defined but it is actually up to the HR partners themselves how they create their roles and how well they understand the business and are able to build the HR agenda around it. One of the company representatives claimed that there are, to some extent, more reactive HR professionals, which by definition leads to HR presenting itself as not strategic. Another interviewee agreed by stating that it is typical for HR to try to help and develop people but this is typically done without being able to link these actions to the overall business.

Welsh et al. (2010) note that HR decisions have heavy strategic implications but because of the intangible nature of these investments it is difficult for decision makers to quantify these implications. Instead of leaning to evidence and hard facts, HR decisions have tended to be based on prior experience and knowledge (Ulrich & Dulebohn 2015). Even thought the prevalent opinion in the case company is that there should not be any other kind of decision-making than fact based decision-making, the reality is not quite there yet.

> *"99% of the whole firms operations are based on rational theory instead of empirical science. Decisions are made while looking into a rear view mirror."*

According to the interviewees, there were no specific triggers why the case company started to promote HR analytics. Instead, it was a sum of many factors. First of all, one of the main reasons was the need and determination to have more transparency when it comes to data. Company representatives stated that it is important to understand the basic elements that are used to lead the workforce and, furthermore, how the whole business is managed through this workforce. HR analytics sheds light to the ways in which the workforce is managed, what are the total costs of the staff, and what are the dynamics in terms of turnover etc. In a way, analytics is in a central role in building the bridge between strategy and management systems. It helps to better understand the underlying realities in order to be able to track down the right and meaningful variables.

> *"Our organization is highly fragmented with multiple separate business areas having operations in dozens of countries and in hundreds of locations. We needed visibility to that."*

Like said, workforce has gone through significant changes in recent times and has become very versatile. Therefore it needs to be managed more efficiently. (Deloitte 2018.) This is in line with the ideas of Fitz-enz & Mattox (2014) as they describe HR analytics as a way to bring together data from distinct sources to best describe the current situation and conditions as well as the probable futures. They also see it as an evidence-based approach assisting companies to make better decisions. (Fitz-enz & Mattox 2014.) In fact, another motive for the adoption of analytics in the case company was the intent to start develop leadership with a more fact-based manner. In other words, the company wanted to be able to validate the theories behind leadership.

All in all, according to the interviews, there exists a consensus on the importance and topicality of HR analytics in the case company. HR analytics is seen as an intriguing topic that is full of potential and business opportunities. In fact, it can be argued that this is a dominant attitude toward the topic among companies in general. A study conducted by Deloitte (2018) supports this argument as it reveals that 71% of participated executives identify HR analytics as important or very important. However, differing opinions and ideas about the current status and meaning of HR analytics are present in the case company. That is understandable as the term "HR analytics" means distinct things to different people. Some people may see it as a process of systematic reporting using a selection of HR metrics while some believe "the only activities and/or processes that constitute HR analytics are those that involve "high-end" predictive modeling". (Bassi 2011.)

> *"Analytics can be described as seeing. Before we only had a dark room with no visibility. Data existed but it had not been collected anywhere. Now the situation is that we have a flashlight that lights a small portion of the room at a time. We try to construct a bigger picture out of these small separate*

> *spotlights but the picture is never completely whole. The goal is to turn on the lights in the room and see everything in real time."*

> *"Analytics is above all mathematics."*

At the moment HR analytics is still in the set-up phase in the case company. To this day, HR analytics has mainly been on the responsibility of one person, who has managed to promote HR analytics to a level where the basic foundation has started to take shape and basic reporting and dashboards are available for HR business partners. Today, the company is able to visualize how their workforce looks like and is also able to maintain the present status. Just like the majority of organizations, the case company is having difficulties maturing from their current state of basic, mostly historical, reporting into more advanced, strategic, and forward-looking analytics. According to Angrave et al. (2016), it is even the big MNCs, like the case company, with lots of resources that are struggling to advance their HR analytics.

> *"[...] As the basics are somewhat in order and technologies are on a appropriate level, we are starting to have the prerequisites for developing our [HR's] strategic capability and workforce simulation possibilities with reasonable expenses."*

One significant reason for the stagnant development of HR analytics in the case company is the prioritization of another big project. A couple of years ago, the company launched a business service center in Central Europe that aims to develop and deliver world-class global business support services in the fields of e.g. finance and human resources. This still ongoing project has been demanding and has required a lot of resources and therefore HR analytics has received less attention. Even though this project can be seen as something that hinders the development of HR analytics it also has another side to it – It can be considered as a strengthener of the necessary basic elements constituting HR analytics.

> *When considering the development HR analytics in Finland, our [the case company's] situation is not hopeless or bad to begin with. The topic is on agenda and we already have certain initiatives and technologies."*

All in all, the case company is in a good place when it comes to HR analytics. Like already mentioned, until this day the company has practiced mainly descriptive HR analytics, meaning the focus has been on what is going on in the organization at a given moment without saying anything about possible future outcomes. Like Edwards & Edwards (2019) point out, there is no question that descriptive analytics would not be useful but the truth is that there are certain limitations. Fitz-enz & Mattox (2014) agree as they say that it is true that descriptive analytics brings less value to an organization than higher-level analytics. However, they highlight that descriptive HR analytics is a prerequisite as it acts as a foundation for more advanced analytics. (Fitz-enz & Mattox 2014.) Therefore, it can be argued that the case company is off to a good start in their analytics journey.

> *"The next step should be to move the focus to the future, that is to shift to a more simulative mode. That way we are able to support the overall business more vigorously."*

4.2. People and their analytical skills and competencies

Isson & Harriot (2016) state that, in addition to using the already existing analytics resources, tools, and technologies, organizations should build a team or a function for HR analytics consisting of people with various backgrounds. McIver et al. (2018) agree that a team should be formed, as it is almost impossible to find an individual possessing all the skills and competencies needed in HR analytics. Like already mentioned, in the case company HR analytics has mainly been on the responsibility of one individual. This individual has, however, been supported by the members of the compensation & benefits –team.

> *"Who is responsible for HR analytics varies a lot among companies. However, it can be argued that it often involves the compensation & benefits –team as it includes people who are more comfortable handling data than rest of the HR population."*

> *"People working in HR tend to be more people oriented than number oriented. Therefore, compensation & benefits –team can be seen as the divergent in the field of HR […]"*

It has been recognized in the case company that in order to move forward with HR analytics, resourcing efforts are required when it comes to people. Interviewees agreed that no individual alone is able to run HR analytics in a company as big as theirs. Instead, there should be a stand-alone team focusing only on HR analytics – It should not be incorporated into any other HR team, like the HR development or compensation & benefits team. It has also been perceived by the company representatives that the team should consist of different roles. Like McIver et al (2018) list, HR analytics requires people that have knowledge on four capability areas: math and statistics, programming and database skills, domain knowledge including HR expertise and behavioral science, and communication and visualization.

> *"Our HR analytics is clearly under-resourced. Analytics builds upon several different roles and those cannot be expected to be filled by a single person. It is too much for one person to develop analytics, uphold reporting, and carry out the role of data scientist at the same time."*

However, it was also explained during the interviews that the organization has not yet resourced people around the topic as they should first decide and more specifically define what is wanted out of higher-level analytics. Forward-looking analytics and workforce planning are part of the case company's strategic HR roadmap, but the aims and targets should be more precisely set and described. When those are in place, it is more worthwhile to make decisions on tools and people required to develop HR analytics. Also Isson & Harriot (2016) recognize the importance of vision as they name it one of the most important building blocks behind HR analytics.

> *"Before we start focusing any more on people, it would be important to more precisely define the vision and aims for HR analytics"*

Once the organization is ready to invest in people the priority is, according to Fitz-enz & Mattox (2014: 36-37), to find the people who have statistical skills but also the enthusiasm and intuitive to go beyond analysis. When considering the qualities and competencies needed by a person working with HR analytics, the company representatives stated that it is important that the person is enthusiastic about data and likes working with it. However, it was recognized that success requires also the ability to see further than the data itself. In fact, one of the interviewees said that liking the data is secondary to being able to make conclusions and clear scenarios based on the data. The interviewee described it as taking a business-consulting role.

> *"Robots can help you to create reports and graphs, but it is only humans who can use these according to the business plan."*

Isson & Harriot (2016) argue that organizations tend to focus too much on the data when it comes to HR analytics. Instead, HR analytics should be seen more as process consisting of inputs, throughputs, and outputs (Fitz-enz & Mattox 2014: 50-52). All of these components require their own set of skills and competencies and therefore, in order to be able provide actionable insights, the case company called for, varied know-how is required. The case company representatives were very doubtful that the required skills could all be found within the HR function. In that they are in line with McIver et al. (2018) who state that organizations usually need to look outside HR when building the HR analytic team with necessary skills, as HR professionals tend to lack understanding on data and analytics. Dulebohn (2015) even declares that many HR professionals choose the field of HR in order to avoid working with numbers.

> *"Data-literacy skills [among HRs] are not on a sufficient level. A person is not born with poor data skills but the reason behind the phenomenon is*

rather the fact that average culture reinforces the average culture. This means that people perform their work as they see others perform it.”

Like already presented in the paper, there has even been discussion about taking HR analytics out of HR (Rasmussen & Ulrich 2015). Based on the interviews, the case company representatives believe that the HR-prefix exists for a reason. According to them, it is crucial to understand the context, meaning it is a completely different thing to conduct analysis on people than it is on e.g. financial metrics or factory performance. In other words, it is believed that know-how on HR is a necessity when conducting analysis on workforce. However, the modernity of the prefix “HR” was questioned during the interviews. One of the representatives called the prefix primitive and misunderstood and told that one of the business areas in the organization even has replaced it with a more modern concept of “people success”.

“The person who deals with HR data has to have an understanding of organizational structures. It is also important to understand that employees are not separate data points in silos but part of teams that are part of the organization. All of this has an effect on how a person acts.”

Even though the interviewees agreed that HR analytics requires knowledge and know-how in the HR domain, they were not against the idea of an organization wide analytics team. Like Rasmussen & Ulrich (2015) state, truly new insights are yielded only if several distinct fields and perspectives are combined together. Therefore, according to them, HR analytics must go beyond HR issues and join the bigger cross-functional business analytics. (Rasmussen & Ulrich 2015.) There have been tentative initiatives in the case company to combine HR data with other functions’ data but so far it has been easier said than done. According to the interviews, it can be argued that in the case organization the functions operate in silos and they all have their own means and ways to conduct business. Therefore, it requires a lot of work to build bridges between them.

”If we want to practice proactive analytics, we have to have close cooperation at least with strategy and finance function.”

Like already noted, HR is often seen as a “soft” line of business (Feather 2008; Tootell et al. 2009). Most of the interviewees questioned the softness of HR by saying, for example, that there is nothing soft about tens of millions of euros going to people’s pays. Therefore, HR professionals should be expected to be somewhat number-oriented, instead of being just people-oriented. It is stated in the prior literature that organizations tend to concentrate only on strengthening and developing the skills of the core analytics team, while it is, in fact, equally important to enhance the data-literacy skills of the whole HR population. (Deloitte 2017a.)

According to the interviewees, the case company has individual HR professionals who understand and utilize data in their work but the overall level of analytical skills and competencies is not yet adequate. This is in accordance with the opinions of Subramanian (2017). He says that HR functions need extra attention in strengthening the analytical abilities. The level analytical capabilities can be increased by hiring new people, but due to the shortage of qualified data scientists with human capital knowledge in the market, it would be better and more effective to train existing staff. (Subramanian 2017.) Lately, the case company has emphasized the importance of former experience and general familiarity with data and analytics in HR related recruiting. Nevertheless, the organization also identifies the need to develop the skills of already existing staff.

> *“[…] Data-literacy skills must be developed, especially now when we aim to move towards more advanced and forward-looking analytics.”*

According to the interviewees, it is central for the case organization to perceive what are the skills and capabilities required from the HR professionals. That is to say, to what extent the know-how is centralized and what is expected to be performed by the HRs them selves. Today’s technology enables the creation of dashboards and other visualizations, which means that a lot of “already chewed” and ready information can be offered to HR professionals. Like already emphasized in this paper, it is central to understand that the goal is not to have all HR professionals able to perform complicated analytical tasks. Instead the idea is to increase the level analytical mind-set and data literacy. (Deloitte 2017a.)

Like one of the interviewees noted, people working in HR are not expected to perform complicated calculations but they need to understand what the data and figures mean and where they are coming from. This statement agrees with the already existing literature where data-literary skills refer to simple data fluency, meaning the familiarity with basic statistical concepts, comprehension of the difference between correlation and causation or practical and statistical importance, ability to slice and dice data based on uncomplicated parameters, and understanding of appropriate data sources and formats. (Deloitte 2017a.) According to the company representatives, there is demand for knowledge and information among HR professionals, but at the same time many also shun it.

> *HR analytics can be seen as a utopia; it exists but no one really knows where and how."*

Like already explained, the case company has recognized the need to form a clearer picture of what is meant by analytics, and more precisely by forward-looking analytics and simulation. Also it is important to have an understanding on how these can be used to support the business HRs and the overall business. Once this kind of elaborated roadmap is in place, the planning and development of analytical capabilities will be easier. According to one of the interviewees, the case company made a mistake in the history and started to acquire people with analytical skills without having the required basics in place. "That showed us that there is no shortcuts to happiness."

4.3. The necessary building blocks behind HR analytics process

According to Isson & Harriot (2016), when creating high-impact analytics it is important to pay attention to the process. Fitz-enz & Mattox (2014) state that analytics processes consist of inputs, throughputs, and outputs and by understanding the correlations between them it is possible to intervene to the two aforementioned in order to improve the outputs. However, organizations tend to focus too much on data. The case company too is guilty of that. Data alone is not enough to bring value to an organization but actionable insights are also needed. (Isson & Harriot 2016.)

> *"We have entered the "world of data". If exaggerated, people seem to think that data will solve all our problems but, unfortunately, the truth is that data by itself does not bring value to the organization. "*

During the interviews it was stated that HR has not really pondered and discussed what are the things that should be known in order to add value to the business. Like literature suggests, the first step should be to identify the critical business questions that need to be answered (Isson & Harriot 2016). While forming these questions, HR function should embrace an outside/inside approach that connects them with the broader business context (Ulrich & Dulebohn 2015). The case company has, in their own words, resourced into strategic HR business capabilities and managed to erect a HR business partner network. In the hopes of identifying crucial business questions, there has been communication with the partners. However, until this day the requests and needs that have come up have been so varied that it has been very difficult to form a reasonable ensemble of analytical contributions. As one of the interviewees suggested, this is arguably due to the poor analytical capabilities of HR business partners and the missing data culture.

> *"[…] Some solutions are only found through questions. It is important for us to have the courage to ask question and also to trust intuition. You do not have to be an analyst to be able to spot critical things. If you are familiar with the business you can get far by using common sense and trusting your intuition."*

It is arguably more or less useless for the case company to delve into individual phases of analytics process if the required building blocks to support the process are not in place and nurtured. Like McIver et al. (2018) state, HR analytics processes are build upon a foundation of three crucial components: workforce analytics capability, workforce analytics vision, and strategic HRM perspective. The paper has already presented and discussed the findings made around HR professionals and their capabilities in the case company. Based on those findings it can be argued that these three aforementioned components are strongly interrelated.

Like already noted, the case company has not invested great deals on people related matters within HR analytics as they feel that they first have to define more thoroughly what HR analytics mean for the organization as well as what is wanted to achieve by it. The already existing literature explains that HR analytics vision provides two crucial aspects. First of all, it acts as a compass that sets the direction and focus for HR analytics and people behind it. Secondly, it creates transparency by communicating the goals of HR analytics for the whole organization. (McIver et al 2018.) During the interviews, the company representatives expressed dissenting opinions about the state of HR analytics vision. The other extreme was a statement that no analytics vision exists in the organization.

> *"There exists no HR analytics vision in the company or if it does it has not been communicated to the whole organization. What is the value of a vision that nobody knows of?"*

According to few interviewees in higher positions, the HR analytics vision is to make all workforce related decisions based on facts. Additionally, the organization also strives to stop glancing into the rearview mirror and move towards more predictive analytics. This too was questioned by some of the company representatives.

> *"The analytics vision is unrealistic and insufficiently defined. It says in the HR strategy that the organization promotes fact-based people management but it feels that the decision makers have no clue what it requires and what is the needed base for making these kinds of future forecasts."*

It is reasoned in the literature that organizations cannot reach their full potential in HR analytics maturity if data-driven decision-making is not embedded in the organizational culture (Deloitte 2017a.) According to McIver et al. (2018), communication around the HR analytics vision emphasizes themes like data-driven insights and expected performance benefits. In the long run, this kind of open communicating arguably leads to the development of data-driven decision-making culture. One of the interviewees stated that the formation of data culture within HR is in breaking point. There are already individuals who are very data-centric and promote the use of data in decision-making. Nevertheless, there are no short cuts. It was suggested more than once during the interviews that examples and positive user experiences could play a huge role in strengthening the data culture within the case organization.

> *"Examples would be very helpful in the creation of HR analytics vision and data culture. Employees should be shown through examples what benefits the usage of data can bring. There is definitely demand for knowledge but there are also people who are shy of it."*

The third important building block behind analytics processes is the existence of strategic HRM perspective. Strategic HRM frameworks and roadmaps focus the attention on important outcomes and elements behind these outcomes. They outline the central variables in a way that gives suggestions about their linkages that could be examined through HR analytics. (McIver et al. 2018.) The case company has HRM roadmap in place and the interviewees stated it to be clear. However, as already referred, HR analytics in the case company today is more reactive than proactive, meaning it is dictated by immediate needs. Therefore, it can be argued that HR analytics is not properly linked to the HRM roadmap.

Other question then is: has the HRM roadmap been properly communicated within the HR population. As these kinds of roadmaps offer a way "to create user buy-in through more short-term immediate impact projects" (McIver et al. 2018), it can be argued that they play a central role in building data culture among HR professionals. If it can be shown that targets are achieved with the help of analytics and data, the overall culture may slowly sift to more data-centric direction. Users are expected to embrace something more eagerly if they experience benefits quickly. (McIver et al. 2018.)

4.4. Technologies supporting HR analytics maturity

In order to enhance HR processes and operations by making it more effortless and faster to access and comprehend key HR and employee data, organizations use HRIS. HRIS software brings together data from a wide range of already existing HR-related databases into a single cloud-based data warehouse. (Angrave et al. 2016.) The case company has already come a long way as they have globally managed to gather most of their HR data under one roof. Before the HRIS project, in order to produce people related reports, data had to be collected from multiple distinct systems and sources and was, therefore, a very time consuming and inefficient process. The HRIS software in use in the case company enables the selection of different modules for talent acquisition, performance management, etc. Also a reporting tool is in place to support the readiness for analytics. Like Jones (2015) states, those solutions and products that do not advertise the readiness for analytics today are scarce. Instead, solutions include reporting tools, which are in most cases incorporated into HRIS. (Jones 2015.)

Even though the company has come a long way and managed to gather most of its people data to one place, there is still work to be done. Like already explained, the case company is a multinational company with operations in dozens of countries. There are certain countries and business areas where the HRIS is seen as a secondary system. That is mainly because the global payroll integration has not yet taken place, meaning payrolls are operated locally.

> *"We have already done great work and managed to get a lot of HR data under the same roof. However there is still work to be done. Payroll integrations are one focal aspect so that we get our salary information up to date. If people do not get their wages they will not come to work the next day which is the reason why payroll systems are the ones being prioritized in countries where payroll integration is not in place."*

> *"Considering their importance, it has taken unreasonably long for payroll integrations to take place."*

According to Angrave et al. (2016), all the major HIRS software, in addition to the usual features, tend to include analytics modules. At the time when HR analytics was initiated in the case company, this was not the case. The HRIS in use did not offer any tools for analytics and therefore the organization was forced to decide on another analytics tool.

> *"The current analytics tool was introduced from necessity, as at that time our HRIS software did not provide ways to visualize data. It was a natural evolution step."*

According to the interviewees, the analytics tool has assisted in visualizing the data and as a result helped to perceive the bigger picture within HR. Moreover, the tool is considered quite user friendly and suitable. However, based on the interviews it can be argued that the tool is still at a development stage. It was stated during the interviews that the analytics solution has been used mainly in reporting needs in which it has performed adequately.

> *"It [the analytics tool] is used for reporting purposes in which it has performed well. However, we should more aggressively calibrate the reporting against its intended use. That way we would benefit more from it."*

> *"We should go through HR user cases in order to understand what kind of information is needed. That way we would be able to build more relevant reports and material."*

The aforementioned quotations also link to the question on how much the case company wants to standardize its HR analytics. In other words, the case organization should determine to what extend HR professionals are expected to find the needed information by themselves and how much ready information is offered to them. Like stated in the already existing literature, HR data is mainly realized by using it to answer critical strategic questions on how people create value for the company (e.g. Rasmussen &

Ulrich 2015; Angrave et al. 2016). This has a lot to do with the skills and capabilities of HR professionals. Like already pointed out, the overall level of analytical skills and competencies is not adequate within the HR profession (Subramanian 2017). This is a statement the case company representatives agreed with. If people are not able to think analytically and do not posses a data-oriented approach, how are they able to tell what they need? Therefore, it can be argued that the efficient use of analytics technologies is highly interrelated with people and their skills and competencies.

Angrave et al. (2016) note that even the big MNCs that have spent enormous amounts of money and resources in HR analytics and have achieved results in analytics in other areas of business admit that their HR analytics programs are stuck in reporting historical information only. In other words, many organizations have failed to develop forward-looking strategic analysis. One reason for that is the fact that analytics modules of HRIS software packages, as they are typically sold and implemented, do not have the capacity to perform this sort of more advanced and forward-looking analysis. (Angrave et al. 2016.) Even though the case company has an analytics tool separate from the HRIS, the problem is the same. According to the interviewees, the current tool is offering a way to visualize data and share it with HR business partner network. It works well for the reporting needs but if the organization desires to strengthen its HR analytics maturity and move towards forecasting and predictive analyses more advanced technological assistance is required.

> *"The current analytics tool is not suitable for creating scenarios and predictions. Due to that, we have already started to screen our options when it comes to new vendors."*

While the amount of data increases, more and more technology companies with solutions to master the data appear on the market (Isson & Harriot 2016). However, according to Sommer (2015) HR departments are not, at the moment, ready for new technologies. He explains himself by pointing out that "new skills, capabilities and insights are needed to make HR more relevant and able to exploit today's new HR technologies". (Sommer 2015.) When asked from the case company representatives whether the skills and competencies of HR professionals are on an adequate level for new technologies, the answer was an unhesitant no. Like already discussed earlier in this paper, the case company has recognized the need to develop the analytical skills and competencies of its staff. However, this is, according to the interviewees, highly interrelated with the organization's HR analytics vision and overall data culture. Therefore, it is possible to argue that also the vision and prevailing culture have their affect on the technological side of HR analytics.

> *"No one is enough interested to voluntarily use their precious time and familiarize themselves with a new system. Instead, nontraditional outputs that require the usage of these systems and tools should be required from people. It definitely requires something more than just acquiring the system or tool."*

In addition to the lack of required analytical capabilities, the reality that HR analytics field is under staffed, causes hindrance in the exploitation of new technologies in the case organization. Like already disclosed by the company representatives, HR analytics involves several distinct roles and therefore it cannot be on the responsibility of one individual. McIver et al. (2018) agree by noting it is almost impossible to find an individual possessing all the skills and competencies required for these roles. Also a study conducted by Deloitte (2017a) supports the formation of a team as result show that organizations with teams devoted to HR analytics tend to be analytically more mature.

> *"One person is not necessarily able to simultaneously develop HR analytics, sustain the reporting, and hold the role of a data scientist. If these different roles are heavily mixed, the development process may not progress as desired."*

In addition to the acquired analytics tool, the interviewees told that Excel is in frequent use in the organization. Like Harris & Gurchensky (2019) note, Excel is the dominant BI application used by organizations. The case company is transitioning from local MS tools into a cloud based G Suite environment, meaning Google Sheet will eventually replace MS Excel. Excel is no longer a standard program available for all the employees. One of the company representatives questioned this during the interviews and argued that as long as data is extracted from HRIS through Excel, it should be available for HR professionals. Like already argued, the presence of data culture and analytics vision encourages people to act and make decisions based on evidence and facts. As average culture reinforces average culture, the utilization of data must become a commonplace practice. For that the tools to acquire data must be in place.

4.5. Data and its governance

Like stated in the already existing literature, analytics can draw insights from both internal as well as external data sources (Deloitte 2011). According to a study conducted by Deloitte (2017a), analytically mature organizations tend to gather data from several data sources in a frequent and timely manner. The case company representatives identified unanimously their HRIS as the most important and most used source of data.

> *"There are multiple data sources available in the organization. Having a centralized HRIS software in place is especially a huge benefit."*

Like already discussed, the case company has come a long way and managed to gather HR related data under one roof. Before investing to the HRIS the data had to be collected from multiple distinct data sources. It took a lot of time and required labor inputs. According to Fitz-enz & Mattox (2014), there are still organizations that house their HR data in multiple distinct systems. In addition to the HRIS, the interviewees listed multiple other data sources they have encountered in their work. These data sources are, among others, surveys, interviews, payroll, LMS, different processes, and third parties. Consequently, it can be argued that there is no shortage of HR related data sources in the case company. Instead, efforts should be addressed to aspects like ensuring the integration between different data sources, collaborating with other functions, and making sure the data is accessible and accurate.

According to Pease et al. (2013), for each data source it is important to be aware how to collaborate with the owner, how to access and integrate the information with other data, and how valid and reliable the data is. Even though technological advancements across the technology industry have made it easier to get hold of information, the technical ways to integrate, organize and analyze data stored in traditional HRIS with data from other sources are not yet fully established. (Angrave et al. 2016.) This is also the reality in the case company. Even though the organization has many sources of HR data, no integration between them exists. Instead, in order to combine, organize, and analyze HRIS data with data from other sources, it has to be first exported as Excel files. Thereafter, the data can be further imported to the analytics tool.

A report published by the SHRM Foundation (2016) identifies inaccurate, inconsistent, or hard-to-access data requiring too much manual manipulation as the biggest obstacle in achieving better use of data, metrics and analysis. In addition to the lack of integration between different data sources, the case company's HR function has not managed to access other functions' data. Like Dulebohn & Johnson (2013) state, workforce planning requires HR and talent data to be integrated with other organizational data, and external data in order to be able perform gap analysis and what-if scenario analysis planning. Thus, it can be argued that the case organization has to strengthen the cooperation between the functions and get rid of the silos restricting the data flow.

> *"When it comes to data, the is no cooperation between the organizational functions yet. However, there has been discussion about merging data from different functions for quite some time now. Especially finance data is something that intrigues us in HR."*

> *We could exploit the finance data sources to a much greater extent. However, that is much more easily said than done because our organization*

> *is split into multiple ´self-governing´ silos. It requires a lot to be able to build anything between them."*

Even though the case company is quite satisfied with their main HR data source, the HRIS, there is still work to be done. The next crucial step, as already argued, would be the payroll integration.

> *"Payroll is one of the important sources of data in HR. In our organization the problem is that we are so fragmented in multiple countries where in all the data looks different and even means dissimilar things."*

Like already stated, the lack of payroll integration is arguably one of the focal reasons why HRIS is considered as a secondary system in some of the countries the case company operates in. That, in turn, has its affect on the accuracy and quality of HR data. As a matter of fact, Andersen (2017) says that bad data is one of the biggest problems when considering the quality of HR analytics. Fitz-enz & Mattox (2014: 80) agree by stating that to any analysis it is essential to have quality data. When data quality was discussed during the interviews with company representatives, the opinions and thoughts around the topic varied quite considerably.

> *"We have taken the step into the `data world´. It seems that the prevalent sentiment in the organization is 'now that we have data we are happy and satisfied'. Data is not an absolute value. We have not really considered what are the things worth knowing and whether those things are trustworthy enough."*

Majority of the interviewees had more negative than positive attitudes toward the level of HR data quality in the case organization. Many of the interviewed company representatives expressed their concerns about the reliability of data. They said that due to the lack of trust in the correctness of data, decision-making is sometimes considered risky.

"When it comes to level of data quality, I have to say that, at the moment, decisions are made with unreasonably large margin of error. There is always a slight undertone: "Assuming these are correct…""

"Data quality is not on a good level. Also I have had personal experience about the lack of defined data definitions and what difficulties it causes."

There were also interviewees who had more positive attitudes toward data quality. According to them, negative attitudes are due to outdated believes and ignorance. The dominant culture within the HR profession does not support efficient and continuous data usage. That conflicts with the idea that data is cleaned through usage.

"In principle, the common opinion is always that the quality of data is poor. I think that our data quality is actually on a quite good level because we have a HRIS and relatively standardized practices. Sure there are many things that require attention and data that could be cleaner but in its entirety everything is on a sufficient level to conduct reasonable analyses."

"*Data quality is arguably one of the biggest obstacles in the minds of HR professionals. It is often heard that either there is no data or the data is not clean. In my opinion, both of these statements are wrong because there is always data available. Data also becomes clean only by using it. Defects in data are spotted by creating connections in it."*

According to Andersen (2017), purely operational approach to data is not enough to insure proper data quality. Instead, a coherent data strategy is needed. (Andersen 2017.) The case company does not have a data strategy in place and some of the interviewees were worried about the fact that there is no one whose daily job is to control data and it accuracy.

"The more we have data the more likely it is that errors occur. Therefore, it is incomprehensible that we do not have employees whose day to day job is

> *to make sure the data is usable."*

However, other measures that have their own effect on the development of data quality have taken a place. Like already mentioned, the company launched a business service center in Central Europe which aims to develop and deliver world-class global business support services in the fields of e.g. finance and human resources.

> *"The business service center is a new way to operate. It introduces country organizations, which help us to standardize our practices and to better the level of data quality. At the moment 55% of our personnel is served by the service center. By the summer that figure should be 80%."*

Like Patre (2016) states, proper data governance ensures that people use analytics as it was intended. Poor or non-existent data governance not only undermines the value of data but also makes it risky to use in any shape or form (Deloitte 2017a). The mistrust is usually due to ineffective governance, which means that the data quality is insufficient to be used in decision-making (Smith & Heffernan 2019.) Analytically mature organizations tend to ensure effective and efficient governance by establishing an organization wide data council or making sure the already existing data council has enough HR representatives (Deloitte 2017a). The data governance in the case company is ineffective, if not even non-existent. At the moment the organization has an IM council but it has not taken any responsibility on data.

> *"We have an IM council. Next step would reasonably be to establish a data council. We also need organization wide data definitions."*

There were differing opinions among the interviewees on how the data governance should be executed. Everybody agreed that the company needs data governance but the question was rather whether it should be organization wide or only within the HR function.

> *"The good question is who should be responsible for data. Our organization*

has a lot of data and its nature differs a lot depending on the intended use. If the whole entirety is tried to be managed, the risk is that things become very bureaucratic. Therefore, a suitable governance model is rather found through usage. Thereafter it is possible to developed and expand it. So, a "bottom-up" process is more advisable."

4.6. The future of HR analytics in the case company

When the case company representatives were asked about the future of HR analytics in the organization, different opinions and views came up. First of all, many of the interviewees stated that the organization has a completely wrong approach to HR analytics. According to them, the goals set for HR analytics are too ambitious with no concrete actions and steps to achieve them. The focus should, instead, be on the fundamentals making sure that they are in order before even dreaming about predictive HR analytics. Like Rasmussen & Ulrich (2015) describe, HR analytics can be seen as a journey. It takes years to form an analytics culture that supports the effective use of HR analytics (Vargas et al. 2018).

> *"When it comes to HR analytics, there has been a lot of fuss and discussion about it but the actual concreteness is missing. Each and every organization should really consider what it is they want to achieve by HR analytics, and how it should be pursued."*

> *"There has been a lot of discussion about predictive analytics and how it should be developed in our organization. In my opinion that is a completely wrong approach as we should first pay attention to fundamentals and make sure we have the data and processes in shape. Once those are in order we can start pursue user cases and basic reporting. In other words, we should do certain kind of data mining and data exploration by HR. That way we slowly move toward more predictive analytics. Predictive analytics should not be seen as something that needs to be pursued but rather as something*

that comes naturally as a result of development."

Madsen & Slåtten (2017) note that there is a lot of hype and buzz around the topic of HR analytics, which has, for one's part, caused it to become a "must have" in organizations. Some of the interviewed company representatives felt that the concept of HR analytics is, in fact, completely overrated. It was boldly stated that predictive HR analytics is made much more complicated than it really is because, in the end, it is all about finding connections and patterns between distinct things. One of the interviewees further argued that common sense should be used. Some answers and solutions are found only by daring to ask questions. According to the interviewee, intuition should also be trusted. It is noted in the already existing literature that intuition and expertise should not be completely forgotten when producing insight to support decision-making (e.g. King 2016). However, nowadays the emphasis should be on basing decisions more on predictive analysis and scientific evidence (e.g. Ulrich & Dulebohn 2015).

> *"All in all, the whole concept of predictive HR analytics is overhyped. In the end we are talking about finding connections (correlations) between things. Those connections can mean that one thing affects the other or not."*

Despite all the differing ideas and feelings on HR analytics' nature, the common opinion among the company representatives was that the company should put the breaks on and really consider what is meant by HR analytics in the organization and what is wanted to achieve by it. Once the purpose and aim are clarified the company can plan and set more concrete actions and milestones. LaValle et al. (2011) note that the implementation steps can be small in the beginning of the journey, as long as they are in line with the agenda.

> *"If predictability is the thing we want to achieve by HR analytics we need a team of HR analytics with people who know mathematics but also understand the field of HR."*

In order to advance the level of HR maturity in the case organization, the company representatives identified few focal aspects to really concentrate on. First of all, the future development requires investment to the people side of HR analytics. Like already discussed, the more advanced HR analytics becomes, the more individuals and different skills and competencies are needed. Secondly, the organization should not rely so much on technologies. Like Andersen (2017) explains, one of the biggest reasons hindering the analytics maturity is bad data and bad data exists due to the assumption that analytics software is the answer. HR analytics software is simply just another data collection tool. "To get the most out of HR analytics you must go through a strategic data process and decide what data are of strategic importance to you and how they ideally look like." (Andersen 2017.) The interviewees agreed that more attention should also be paid on data and its quality.

> *"No tool or software will bring solutions but resourcing and organization in the background are equally important."*

> *"Attention should be paid on data structure's processes and use purposes. Regardless of technology, those problems will not disappear."*

5. CONCLUSIONS

The purpose of this thesis is to examine the current status of HR analytics and the factors hindering its maturing in the case company. Furthermore, the aim is to identify the key-factors in building HR analytics maturity. This final part of the paper presents and summarizes the main findings of the study and discusses the theoretical and managerial contributions. Lastly, the limitations of the research are pondered and suggestions for future research are given.

5.1. Key findings of the study

The case company initially introduced HR analytics in order to get a better picture on what was going on in their highly fragmented organization. When viewing the "technical" stages of HR analytics maturity, based on the findings it can be argued that the case company is conducting descriptive analytics. Until this day, the case organization has not been able to move from basic reporting, where the focus is on historical and current events, to more advanced and forward-looking analytics. However, nowadays the focus has shifted from the already presented more "technical" stages of HR analytics to organizational enablement, culture, and skills development (Deloitte 2017a). In order to be able to define the maturity level, on which the case company is on, the findings regarding the identified factors effecting HR analytics need to be summarized

The findings suggest that there are multiple factors affecting the maturity of HR analytics. Therefore, also the hindering factors can be numerous. In order to guarantee the success in HR analytics development and maturing, it is essential to have all the required elements at a reasonable level simultaneously. These elements are meaningful applications, accessible and good quality data, the tools and capabilities to exploit the available data, and the competencies to conduct analysis and offer insights to guide actions. Moreover, it is crucial to fight against the hesitation decision makers have against the usage of HR data and analysis. Instead of trusting intuition and former experience in the workforce related business decisions, HR should take a more data-centric approach and that way get slowly rid of the “soft” prefix.

When it comes to people, based on the findings it can be argued that HR analytics is under-resourced in the case company. At the moment the organization does not have a team dedicated to HR analytics but, instead, the responsibility is on one individual. If the case organization strives to better the maturity of its HR analytics, it should involve more people to the process as it is almost impossible for one person to fill all the roles required. Moreover, the skills and competencies among the rest of the HR population are not on an adequate level. Therefore, it is essential for the case company to continue concentrating on data-literacy and analytical skills in their recruitments. Moreover, the possibilities and opportunities for the already existing HR staff to develop their analytical skills should be increased.

The technological aspect of HR analytics in the case company is arguably at a satisfactory stage. The company has come a long way in gathering its HR data under one roof by building a HRIS system. In addition, the case company also has multiple other sources of data, like different surveys and third parties. Therefore, it can be claimed that there is HR related data available in the organization. Nonetheless, efforts should be addressed to aspects like ensuring the integration between different data sources, collaborating with other functions, and making sure the data is accessible and accurate. The case company has also acquired a tool to analyze the available data. Therefore, based on the findings made during the interviews, it can be argued that the technological aspect cannot be considered as a hinderer in building HR analytics maturity in the case company. It is rather the lack of needed analytical skills and competencies that prevents the proper and effective use of these technologies. Thus, the company should really consider filling the existing skill gap before acquiring new technologies.

In addition to the skills and competencies, another focal factor hindering the HR analytics development in the case company is the way data governance is organized – it is almost non-existent. The organization representatives stated that the usage of HR data in decision-making is experienced risky, as there are no established procedures to guarantee the accuracy and quality of the data. At the moment, there is no one in the case company whose day-to-day job is to monitor, control, and develop the accessibility and correctness of data. However, the fact that the case company launched a business service center that aims to develop and deliver world-class global business support services in the fields of e.g. finance and human resources, may offer a good opportunity for the organization to develop its HR data governance models and actions. It is not ruled out that, in the long run, a cross-functional data council could be developed in order to guarantee effective data governance. However, the organization should start small and first concentrate on the HR data. Like one of the interviewees noted, the best governance model is found through usage and little by little it is possible to develop and expand it.

Like the findings suggest, the five identified factors affecting HR analytics maturity are highly interconnected. Based on the findings from the interviews, few factors seemed to have an effect on all the others: data culture and vision. It can be stated, based on the findings, that the case company is missing a prevalent data culture and a vision for HR analytics. The case company has not defined what is meant by HR analytics, which in turn makes it really hard to create a roadmap with realistic milestones. The lack of vision, for one's part, also hinders the formation of data-driven decision-making culture as communication around the analytics vision enforces the data-driven culture. Also, the fact that no HR analytics vision exists makes the development of other analytical key-factors difficult. Therefore, it is crucial that the case organization really defines what it wants to achieve by HR analytics and thereafter sets a realistic roadmap with achievable milestones.

Instead of just aiming for predictive HR analytics, the case company should take a more composed approach. In other words, the organizations should but on the break and really concentrate on the basics behind HR analytics. Like it was noted during the interviews, predictive analytics should not be eagerly pursued but it should rather be seen as something that comes naturally with time and development. That is to say, there are no shortcuts. Instead, HR analytics can be seen as a journey and it takes years to reach the high levels of maturity. Like already argued, when considering the more technical stages of HR analytics, the case company today is conducting descriptive analytics. When viewing the maturity scale referring to organizational enablement, culture, and skills development, the findings indicate that the case company has reached the second level, which is called as “consolidating and building”. That is because the organization has understood the importance and value of people related data and has invested in the different sectors and factors of HR analytics. However, in order to move to the third level of analytics maturity, efforts and actions are needed. Suggestion for upcoming measures and procedures are given next.

5.2. Managerial implications

Few of the biggest hinderers in the case company are the lack of data-driven decision-making culture and HR analytics vision. Therefore, the organization should, first of all, start to communicate more the importance of data-driven decision-making and the significance of data in bringing value to the firm and in competing in the marketplace. Moreover, the company should work on a defined HR analytics roadmap with milestones for the next few years. Once the roadmap is sketched, the core HR analytics team should be formed in order to have all the required and needed skills to move forward on the maturity scale. The rest of the HR population should not be ignored but the organization should begin to think of ways to increase their basic data literacy skills.

The technical components behind HR analytics are at a decent stage in the case company. Instead of considering purchasing new tools and solutions, the firm should, in the near future, rather concentrate on the integration capabilities of the already existing tools and solutions. Focus should also be on strengthening the delivery mechanisms in order to make HR data available for everyone who seeks it. Moreover, the case organization should investigate the possibilities to incorporate non-HR data into people data. Lastly, the case company is suggested to ponder who should be responsible for creating and overlooking standard HR data practices in the future in order to guarantee consistent and reliable data inputs needed in efficiently functioning analytics process.

5.3. Theoretical contributions

This thesis contributes to the existing literature and research in the field of HR analytics. Like already stated, the topic has gained limited attention among management researchers (Marler & Boudreau 2017). The scarce studies are "often published by consultants with a commercial interest in the HR analytics market" (Rasmussen & Ulrich 2015), with very little guidance and information how to translate ideas into practice (King 2016). By interviewing the company representatives, this paper managed to obtain a quite thorough understanding of the current state of HR analytics and factors affecting its maturity in the case organization. Based on the findings, the thesis gives practical suggestions on how to build HR analytics maturity.

The findings from previous research suggest that there are five main factors that can be seen affecting the maturity of HR analytics: people and their analytical competencies, processes, technology, data, and governance. The already existing literature also suggests that each of these factor groups also include possible maturity hinderers. (e.g. Deloitte 2011; Isson & Harriot 2016.) This study agrees with the previous ones and identifies the lack of analytical team and skills (e.g. Andersen 2017; Dahlbom et al. 2019), missing data culture (e.g. Deloitte2017a), putting too much trust on technology, poor data quality (e.g. Andersen 2017), and lack of data governance (e.g. Smith & Heffernan 2019) as the most significant hindering factors. However, unlike former studies, this thesis highlights the importance of present and realistic HR analytics vision. This paper identifies the lack of analytics vision as the most pivotal hinderer of HR analytics maturity as the findings indicate that it has a direct or indirect effect on all the other factors impacting HR analytics. HR analytics vision, in a way, acts as a guide on the HR analytics journey as it instructs organizations in their decisions and investments around the topic.

Furthermore, as opposed to the already existing literature, this paper emphasizes that all these five factors affecting HR analytics maturity are interrelated, meaning they cannot be regarded as separate and stand-alone variables. Instead, they all need to be scrutinized and developed hand in hand. For example, investments in new analytics technology and tools are arguably useless if the skills and competencies of people are not on a required level. Also, poor data quality always results in untrustworthy and insufficient outcomes despite the technologies and tools in use. Therefore, based on these examples, it can also be stated that a hierarchy among these five factors exists, meaning that some of the factors can be regarded as more essential than the others – especially in the beginning of analytics journey. Thus, it is arguably profitable to weigh the importance of each factor in a relation to others in order to guarantee the best outcomes of every investment and development action.

5.4. Limitations of the study and suggestions for future research

The most important limitations of this study stem from the employed methodological choices. As the aim of this thesis is to obtain a comprehensive understanding of the current state of HR analytics and the factors affecting its maturity in one certain MNC, the paper follows a qualitative research approach. More precisely, the research strategy used in this thesis is an intensive case study. As an "intensive case study research aims at understanding the case from the inside by providing a thick, holistic and contextualized description and interpretation" (Eriksson & Kovalainen 2016: 133), it can be agued that the purpose of this paper is not to produce generalized results.

One other focal limitation of the study relates to the selected sample. Most of the interviewed company representatives were on relatively high positions in the organizations. Therefore, it can be argued that the findings present only the viewpoint of a small portion of case company's HR population, telling very little about the positions and opinions of the "end users" of HR analytics.

As HR analytics has gained limited attention among management researchers (Marler & Boudreau 2017), the possibilities for future research are considerably manifold. As this study examines the status of HR analytics in one particular MNC it would be meaningful and interesting, as a future study, to expand the scope and research several international organizations in Finland in order to get more generalized results on the state of HR analytics in the Finnish context. Furthermore, it could arguably be informative to compare these results with the findings from different countries. Moreover, the case company could extend the research over the boarders of HR and investigate the state of analytics in other functions. These findings would arguably give suggestion and guidance how to proceed with HR analytics development. Additionally, this kind of cross-functional study could also bring the organization together by diminishing the gaps between functional silos.

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APPENDIX - Guiding questions for the interviews

Category	**Questions**
Interviewee information	○ What are your role and responsibilities in the company? ○ How would you define your role when it comes to HR analytics specifically?
Background/general information	○ What was the trigger for paying more attention to HR Analytics in your company? ○ What are the main goals of HR analytics in your company? ○ How would you describe the current level of HR analytics in you organization?
People and teams in HR analytics	○ Who are the ones responsible for HR Analytics? ○ What is the current level of data literacy and analytical skills among HR professionals? ○ Are there opportunities available for employees to develop themselves in that area?
HR analytics processes	○ Is there an outlined process for HR analytics? ○ Do you feel there's an analytics vision in place in the organization? How about a strategic HRM framework/roadmap?
Technologies in HR analytics	○ What specific systems or tools are used in HR reporting and analytics? Are they working well for the company's needs?
Data in HR analytics	○ What are the internal or external data sources used in HR analytics? Are these easy to access and get data from? ○ Is the level of data quality adequate?
Governance in HR analytics	○ Does your organization have a data council? ○ Are there common data definitions in place in the company?
Future of HR analytics	○ In your opinion, what are the biggest factors that need attention when it comes to HR analytics? ○ What kind of plans the company has in order to tackle challenges related to HR analytics?