THE USE OF HR ANALYTICS IN THE FINANCIAL INDUSTRY

Case study: Banking sector

Lappeenranta–Lahti University of Technology LUT

Master's thesis in Business Analytics

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ABSTRACT

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This thesis conducts a case study on HR analytics in a Finnish bank, company X. The key concepts for fluent adoption and implementation of HR analytics are identified by examining the topic first from a theoretical perspective through a literature review. The key concepts of employee competence with respect to analytical and reporting skills, employee performance measurement, evidence-based management culture and communication of the results, HR data quality, privacy and utilization of various data sources, analytics maturity levels, methods and tools as well as HR metrics classification and the implications of the organizational strategy on analytics are utilized in the empirical part of the thesis where the current situation of the case company is discussed and evaluated. Finally, the thesis provides improvement suggestions for further development of the case company's HR analytics.

The study's findings indicate that the case company mainly uses descriptive-level analytics, consisting of HR metrics reported with Excel which also coincides with the level of employee competence. At present, only internal HR data sources are utilized in reporting, and data quality control is irregular. Although data privacy is carefully monitored by industry- and company-specific laws and regulations, it also poses challenges for combining data from different departments within the organization. As improvement suggestions, this thesis recommends increasing the employee competence in analytics and statistical skills, regular data quality monitoring, more versatile combining of data sources and the implementation of more sophisticated analytics tools and methods.

This study contributes to the current literature by providing a comprehensive overview of the situation inside a single company while the extant literature focuses on studying a single phenomenon within a larger sample of case companies. The results obtained suggest that while the interest towards HR analytics is on the rise, the implementation of it has not yet reached its full potential.

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Tämä opinnäytetyö toteuttaa yksittäisen tapaustutkimuksen HR-analytiikan käytöstä suomalaisessa pankissa, yrityksessä X. HR-analytiikan sujuvan käyttöönoton ja toteuttamisen avainkäsitteet ja organisaatiovaatimukset tunnistetaan tarkastelemalla aihetta ensin teoreettisesta näkökulmasta teoreettisen viitekehyksen ja kirjallisuuskatsauksen avulla. Näitä avainkäsitteitä hyödynnetään opinnäytetyön empiirisessä osassa, jossa raportoidaan ensin case-yrityksen nykytilanne, jonka jälkeen nykyisestä tilanteesta annetaan teoriaan pohjautuva arvio. Lopuksi opinnäytetyö esittää parannusehdotuksia HR-analytiikan kehittämiseksi edelleen.

Tutkimuksen tulokset osoittavat, että case-yrityksessä käytetään tällä hetkellä pääasiassa kuvailevan tason analytiikkaa, joka koostuu Excelillä raportoitavista HR-mittareista. Tällä hetkellä raportoinnissa hyödynnetään sisäisiä HR-lähteitä, ja datan laadunvalvonta on epäsäännöllistä. Vaikka tietosuoja huomioidaan tarkasti jo alakohtaisten lakien ja säädösten kautta, aiheuttaa se myös haasteita tietojen yhdistämisessä organisaation eri osastojen välillä. Parannusehdotuksina tämä opinnäytetyö suosittelee työntekijöiden taitojen kehittämistä analytiikan ja tilastotaitojen saralla, säännöllistä datan laadun seurantaa, monipuolisempaa tietolähteiden yhdistämistä sekä kehittyneempien analytiikkatyökalujen ja -menetelmien käyttöönottoa.

Tämä tutkimus täydentää olemassa olevaa kirjallisuutta tarjoamalla kattavan yleiskatsauksen yhden yrityksen tilanteesta, kun taas aiempi kirjallisuus keskittyy tutkimaan yhtä ilmiötä suuremmassa tapausyritysten otoksessa. Tulokset viittaavat siihen, että vaikka kiinnostus HR-analytiikkaa kohtaan on kasvussa, sen toteutus ei ole vielä saavuttanut täyttä potentiaaliaan.

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1 Introduction

HR analytics is discussed by multiple studies as a novel method offering organizations the possibility to impact organizational performance and thus gaining competitive advantage (Bassi 2012, 15; Bonilla-Chaves & Palos-Sánchez 2023, 1; Davenport et al. 2010, 54; Ghatak 2022, 7; Marler & Boudreau 2017, 17; Minbaeva 2017, 709; Saramies & Törnroos 2021, 34-35; Shet et al. 2021, 320). This thesis aims to contribute to the research of HR analytics in the financial industry through conducting a qualitative case study in company X. As we move towards a more knowledge-intensive society, the decisions made in organizations are increasingly based on data. Evidence-based management, and investing in analytics, is not new amongst most of the organization's departments, but since recently it has stayed out of the reach of HR. Traditionally, decisions made inside HR have been based on intuition (Chalutz 2019, 1429; Dahlbom et al. 2020, 134, 135; Ghatak 2022, 5, 232; King 2016, 490; Murphy & Zandvakili 2000, 94; Rasmussen & Ulrich 2015, 236; Saramies & Törnroos 33-34), which is in stark contrast with the goals of the present knowledge-intensive culture. However, HR analytics aims to take HR to the same level with the other business functions and help HR to transfer its role into a more strategic one. Even though organizations have recognized the importance of their employees in gaining competitive advantage already some time ago, the paradox of not investing enough in this asset to fully understand it remains (Ghatak 2022, vii). Besides this, creating a valuable employee experience and thus retaining talent in company has developed into a new must in today's work market (Huselid 2018, 679). HR analytics can prove to be the way to achieve all this (Margherita 2022, 10).

According to Finance Finland (FFI, suom. Finanssiala ry), the representative organization of the operators of the Finnish financial sector, there were 12 banks operating in the sector employing over 21 000 people at the end of 2023. Even though this figure includes foreign deposit-taking banks' offices in Finland, the role of Finnish banking sector as an employer is nationally significant. (Kettunen, Finance Finland 2024) Also, the evidence-based management and decision-making is natural inside banks as it is part of the characteristics of the industry. However, like in organizations in general, the level of decisions made based on data is traditionally lower in HR than in other departments such as finance. Therefore, studying the use of HR analytics in the Finnish financial industry can be considered an important topic as well.

Previous research conducted on HR analytics in the financial industry has been scarce. There were three studies identified addressing the topic through the literature review process, two of which utilized linear modelling in identifying the determinants of absenteeism and the performance of a bank on a branch level, the third study examining the KPIs of four banks with respect to level and focus of reporting between intellectual capital (IC) and corporate social responsibility (CSR). In their study Kristensen, Jørn Juhl, Eskildsen, Nielsen, Frederiksen & Bisgaard (2006) proved the relationship between absenteeism and job satisfaction using a linear regression model. In addition, they showed that specific demographical factors such as the age and gender as well as the absence behaviour of the team manager impacts also the absence behaviour of the team members. Bartel (2004) studied the performance of a bank on a branch level specifically utilizing the dimensions of a high-performance work system to model the HRM environment of the bank. In this study it was shown that the incentives dimension had a significant positive relationship with the performance. The study by Cuganesan (2006) showed that there are differences between the number and focus of KPIs reported by the four biggest banks of Australia. While the CSR was the more common approach, also IC was used. This finding goes to show that at least amongst the participants of this sample group, the value created for stakeholders is considered more important than the value generated by human capital.

Despite the growing interest in HR analytics, there is notable lack of research on utilization of it in the financial industry. The lack of research probably results from the fact that HR analytics is still considered an emerging concept, thus the research has not specialized in single industries yet (Chalutz 2019, 1430, 1441; Marler & Boudreau 2017, 6, 13-14). Also, the financial industry is commonly known of strict data governance policies and bounding legislation, therefore affecting the information published of research conducted in organizations operating within the industry. This is combined with the fact that company workforce, especially in the knowledge-intensive organizations, is cited by many researchers as key contributor to organizational performance and competitive advantage (Chalutz 2019, 1429; Jääskeläinen & Laihonen 2013, 350-352; Tootell et al 2009, 377). This thesis aims to contribute in breaching this research gap by studying the use of HR analytics in a Finnish bank.

1.1 Scope of the study

As this thesis was conducted in co-operation with a case company, the scope of the study was primarily determined by the HR analytics development project of company X, which was at the initial phase. The aforementioned research set-up dictated also the methodological scope of this study since the HR analytics development project in company X was only about to start. Therefore, it was reasonable to conduct a qualitative study to examine the current situation of the company and make general suggestions about the forthcoming steps in developing HR analytics. In addition to this limitation, qualitative method was deemed suitable for examining the current situation on a more general level. Due to these aspects, this study represents a qualitative study with primary data collection conducted through semi-structured interviews and secondary data collected through internal HR report descriptions provided by the case company. The limitations to the scope of the study are presented in full in Figure 1.

Figure 1. Scope of the study.

In terms of topic scope, this thesis aims to study the current use of quantification in HRM with a focus on HR metrics and HR analytics in the case company. Therefore, other aspects of HRM are not discussed as they are beyond the scope of this study. In addition to studying the current state of the case company, general development and improvement suggestions are also given in the conclusive part of this thesis. Since this thesis serves as a preliminary study, the development suggestions made are presented on a more general level and do not include in-depth process descriptions and detailed advice with the exception of an example case discussing the means of solving one organizational challenge introduced by the case company. Also in this case, since concrete work with data was out of the scope of this study, some suggestions given might not be applicable in some cases.

1.2 Research questions

This thesis aims to contribute to the research gap identified in the use of HR analytics in the field of financial industry. It aims to offer the case company an evaluation of their current situation with respect to the subject, while also offering suggestions how HR analytics could be developed further inside the company. To reach this goal, theoretical knowledge of the subject is collected through conducting a comprehensive literature review and studying the subject from various aspects in the form of a theoretical framework.

The first research question demands conducting a literature review aiming to identify the earlier research conducted on HR analytics in the financial industry. Since the research conducted on HR analytics in the financial industry was identified scarce already through preliminary examination of the topic, the literature research of this study was decided to be expanded to include knowledge-intensive organizations due to their similar characteristics with the financial industry. In addition, it was also decided to include theoretical information on other HRM quantification approaches to widen the understanding of how HRM practices are evaluated quantitively in the chosen industries. This was deemed beneficial from the case company point of view to offer a more comprehensive overview how HRM practices can be linked with organizational performance. After specifying the industry-wise scope with the expansion of HRM quantification approaches, the assumption was that through the theoretical framework and literature review an unknown number of key concepts would be identified. These key concepts would be used as a frame in evaluating the current situation of the case company. Therefore, the first research question of this thesis was formed as:

RQ1: What kind of HR analytics or HR metrics solutions and other HRM quantification approaches exist in the financial industry or in the knowledge-intensive organizations? What are the key concepts of these?

Since this thesis is conducted as a qualitative case study in co-operation with a case company, forming a comprehensive picture of the company's current situation with respect to HR analytics and the key concepts identified through the theoretical part is relevant. In addition to the evaluation, the primary goal of thesis is to provide the case company with improvement suggestions on how to develop their HR analytics further. To reach this goal, theoretical knowledge gained from the literature review and the evaluation of the case company's current situation determined in the empirical part are combined. Hence, the second research question is stated as:

RQ2: What is the current state of HR analytics in company X and how could it be developed further?

1.3 Thesis structure

This thesis begins by introducing the topic of the study as well as its importance and relevance for financial industry in the current world situation. The introductory part includes also a definition of the scope of the study with its limitations. This is followed by stating the research questions aimed to be answered in this thesis and the process leading into expressing them in the specific form they are stated in. The first chapter ends with presenting the thesis structure summarising the main aspects of each chapter as well as illustrating in Figure 2 the division of the thesis into theoretical and empirical parts.

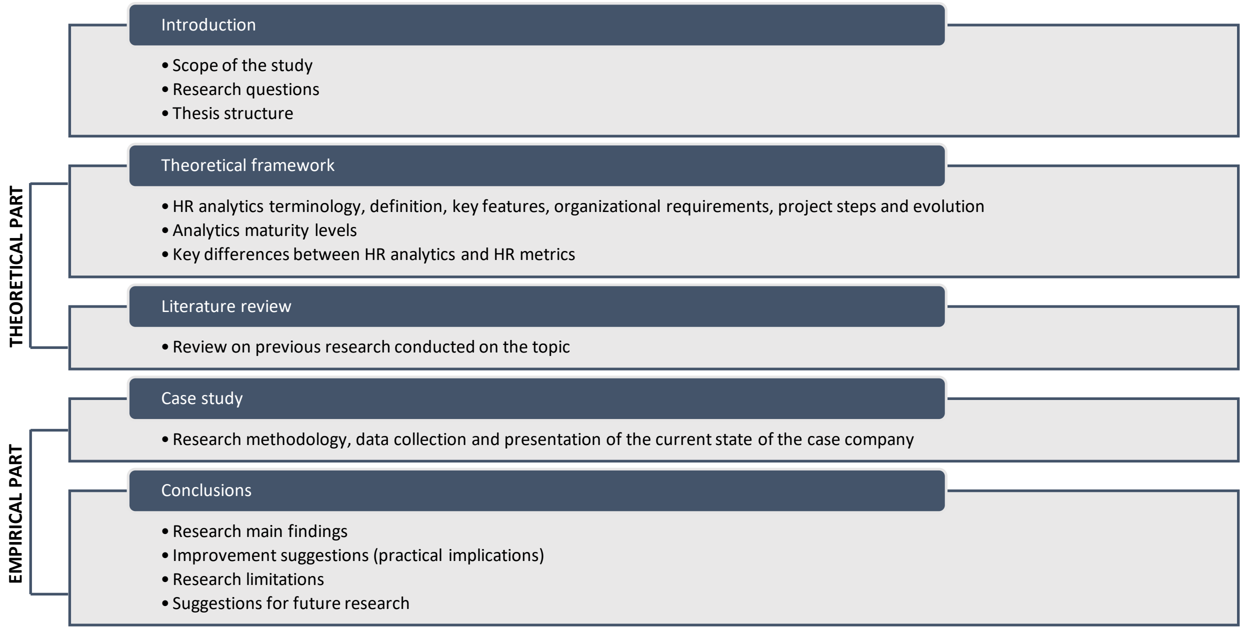

Figure 2. Structure of the thesis.

The theoretical part of this thesis begins with theoretical framework which aims to present the phenomenon of HR analytics comprehensively. This is conducted through discussing the still ambiguous terminology and the various definitions presented by previous researchers in addition with suggesting an own definition for the phenomenon. Furthermore, the key features associated with HR analytics are presented with the organizational requirements for successful adoption and execution of HR analytics. The chapter is completed by discussing the steps or phases of a typical HR analytics project along with a brief look into the evolution of the phenomenon. The theoretical part is then continued with a literature review presenting the previous research conducted on the topic. The key concepts used in forming the frame for the interview questions in the empirical part are identified through the theoretical framework and the literature review.

As stated before, the theoretical part of this thesis is used as the frame for the execution of the case study in the empirical part. The empirical part is carried out as a qualitative single case study. First, the methodological choices and limitations resulting into this decision are discussed in the beginning of this chapter followed by introducing the data collection methods used. Empirical part continues by giving an in-depth report of the current state of the HR reporting and analytics in the case company on various aspects. In the conclusive chapter ending the empirical part, the current state of the case company is evaluated with respect to the key concepts identified through the theoretical part. In addition to this, improvement suggestions and practical implications for developing the HR analytics in the case company are discussed. Finally, a summary of the thesis discussing the key findings along with research implications and limitations are presented with some suggestions for future research topics.

2 Theoretical framework

The theoretical framework of this thesis covers the most important aspects related to HR analytics. It begins by taking a brief look at the ambiguous terminology of HR analytics and continues by introducing and explaining the key features involved, as well as the requirements for a successful implication of HR analytics. This is followed by presenting the phases of a typical HR analytics project before briefly going through the evolution of the phenomenon. Finally, the maturity levels of analytics are presented and the key differences between HR metrics and HR analytics are stated.

2.1 HR analytics terminology

Terms HR analytics, people analytics, talent analytics and workforce analytics are often used to describe the same phenomenon. Since HR analytics is still considered to be an emerging concept, the terminology used in the literature is incoherent. (Bonilla-Chaves & Palos-Sánchez 2023, 1-2; Chalutz 2019, 1430; Huselid 2018, 680; McCartney & Fu 2022, 27, 41) As a part of their research Tursunbayeva, Di Lauro & Pagliari (2018, 225-226) studied the relative popularity of online searches for the seven most popular terms in Google Trends between the timeframe of 2004 and beginning of 2018. In this research it was discovered that initially the search terms “human resource analytics”, “HR analytics” and “workforce analytics” were most popularly used, but by 2008 searches related with “people analytics” and “HR analytics” had become clearly the two most popular ones (Tursunbayeva et al. 2018, 226).

Inspired by this research aspect, an update was conducted for the purposes of this thesis. This involved using the five most used search terms cited in the findings of Tursunbayeva et al.’s research to discover the current worldwide situation between the timeframe of 2018 and early 2024. The findings of this overview conducted with Google Trends are presented in Figure 3, clearly showing that the terms “HR analytics” and “people analytics” are still the most popular ones used by far. Currently, the relative popularity of these two terms is almost identical, “people analytics” having a score of 79 and “HR analytics” 80. According to Google Trends’ scoring description, “Numbers represent search interest relative to the highest point on the chart for the given region and time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. Likewise, a score of 0 means the term was less than 1% as popular as the peak.” This result coincides with the insights of research conducted by Bonilla-Chaves & Pálos-Sanchez (2023, 18-19) of HR analytics and people analytics being the two most popular keywords used in also scientific literature of HR analytics.

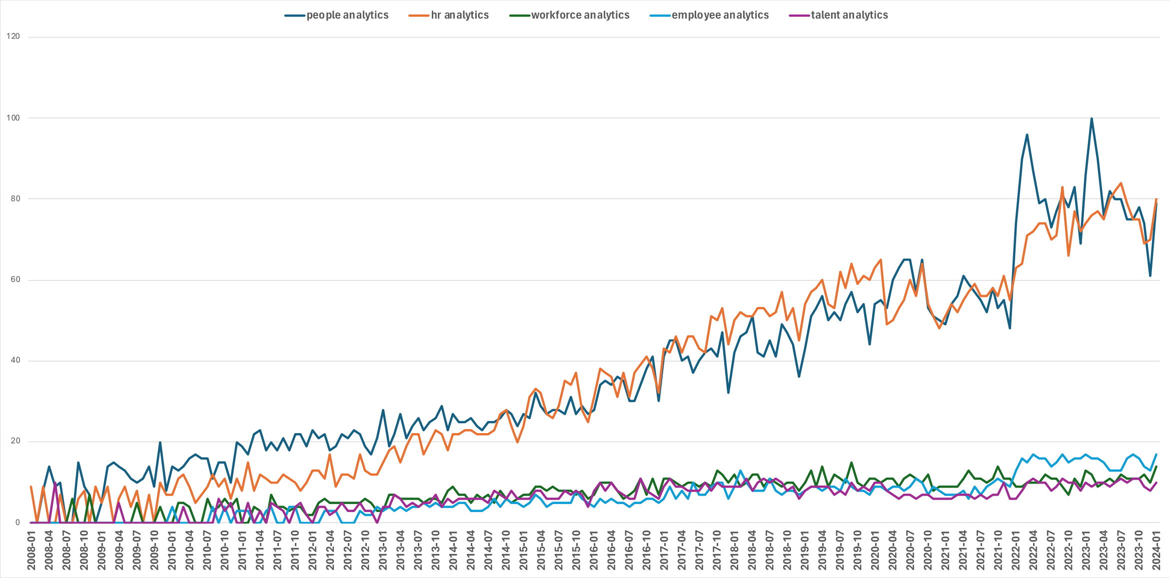

Figure 3. Selected keywords that describe the relative popularity of each keyword compared to each other.

In addition to insights obtained by the overview conducted, Marler & Boudreau (2017, 7), Melo & Machado (2021, 5) and Bonilla-Chaves & Pálos-Sanchez (2023, 19) state in their research that out of these two HR analytics seems to be the most frequently used term amongst the scientific literature. Based on these findings, the use of both terms could be justified, but this thesis concentrates on using the term HR analytics.

2.2 Definition for HR analytics

The definition of the term HR analytics is not unequivocally explainable (Chalutz 2019, 1430; Fernandez & Gallardo-Gallardo 2021, 166; Huselid 2018, 680; Marler & Boudreau, 2017, 4, 7). While many studies conducted during past years have contributed into forming a complete definition, there is still a lot of ambiguity present, as there is also with the terminology (Falletta & Combs 2021, 52; Fernandez & Gallardo-Gallardo 2021, 168). In the earlier research, HR analytics was defined as a narrower phenomenon concentrating on employee and technical scopes primarily, while later studies have expanded the scope to underline the strategic perspective as well (Chalutz 2019, 1432). Table 1 presents some definitions used in the academic literature over the time span of almost 20 years. What is common to almost all of them, is the reference of using people related data and HR decisions in some form to impact organizational performance. This summary seems to form the frame of the definitions despite the terminology and year of publication of the source, a notice made also by Fernandez & Gallardo-Gallardo (2021) in their research.

Table 1. Different definitions of HR analytics presented in the academic literature.

No	Article / publication	Year	Author	Term used	Definition
1	HR Metrics and Analytics: Use and Impact	2004	Lawler et al.	HR analytics	The use of analytics in order to understand the impact of HR practices and policies on organizational performance. Statistical techniques and experimental approaches can be used to tease out the causal relationship between particular HR practices and such performance metrics as customer satisfaction, sales per employee, and, of course, the profitability of particular business activities.
2	Predicting People: From Metrics to Analytics	2009	Fitz-enz J.	Human-capital analytics	A method of logical analysis that uses objective business data as a basis for reasoning, discussion, or calculation.
3	HR Analytics Handbook: Report of the State of Knowledge	2010	Bassi et al.	HR analytics	The application of a methodology and integrated process for improving the quality of people-related decisions for the purpose of improving individual and/or organizational performance.
4	An evidence-based review of HR Analytics	2017	Marler J. & Boudreau J.	HR analytics	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.
5	The rise (and fall?) of HR Analytics	2017	van den Heuvel S. & Bondarouk T.	HR analytics	The systematic identification and quantification of the people-drivers of business outcomes, with the purpose of making better decisions.
6	The science and practice of workforce analytics: Introduction to the HRM special issue	2018	Huselid A.	Workforce analytics	Workforce Analytics refers to the processes involved with understanding, quantifying, managing, and improving the role of talent in the execution of strategy and the creation of value. It includes not only a focus on metrics (e.g., what do we need to measure about our workforce?), but also analytics (e.g., how do we manage and improve the metrics we deem to be critical for business success?).
7	Redefining HR using people analytics: the case of Google	2018	Shrivastava et al.	People analytics	Refers to the use of analytical techniques such as data mining, predictive analytics and contextual analytics to enable managers to take better decisions related to their workforce.
8	People Analytics -A scoping review of conceptual boundaries and value propositions	2018	Tursunbayeva et al.	People analytics	An area of HRM practice, research and innovation concerned with the use of information technologies, descriptive and predictive data analytics and visualisation tools for generating actionable insights about workforce dynamics, human capital, and individual and team performance that can be used strategically to optimise organisational effectiveness, efficiency and outcomes, and improve employee experience.
9	The HR analytics cycle: a seven-step process for building evidence-based and ethical HR analytics capabilities	2021	Falletta S. & Combs W.	HR analytics	A proactive and systematic process for ethically gathering, analyzing, communicating and using evidence-based HR research and analytical insights to help organizations achieve their strategic objectives.
10	Exploring the Evolution of Human Resource Analytics: A Bibliometric Study	2023	Bonilla-Chaves E. & Palos-Sánchez P.	HR analytics	A novel system to collect, analyze, and present this (the composition of the group of human capital resources, the specification of required behaviours, and the measurement of the effectiveness of the decisions derived from the various business strategies and/or competitive situations encountered) information from organizations.

After performing an integrative synthesis of published peer-reviewed literature on the topic, Marler and Boudreau (2017, 13) define HR analytics as follows,

> “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.”

This definition has been used and cited by many scholars and authors since (Dahlbom, Siikanen, Sajasalo & Järvenpää 2020; McCartney & Fu 2022; Saramies & Törnroos 2021; Wang, Zhou, Sanders, Marler & Zou 2023), indicating that it is found to be a comprehensive description of the topic. Out of these, a systematic literature review done by Wang et al. in 2023 also adopts this definition, implicating that it still is considered up-to-date (Wang et al. 2023, 1).

Since the core idea of HR analytics is about linking HR data to organizational performance and outcomes thus gaining new, valuable insights, there is a need for utilizing and linking data from various departments of the organization in addition to HR (Rasmussen & Ulrich 2015, 238). Therefore, this thesis adopts the following definition for HR analytics,

A process of utilizing various techniques to convey valuable insights gained through linking HR data with data from organization’s other departments for evidence-based decision-making and management to improve organizational performance.

2.3 Key features of HR analytics

Saramies & Törnroos (2021, 33) offer a reasoning which might explain why many scholars cite and adopt the definition formed by Marler and Boudreau (2017). They state that the definition highlights the key features that describe HR analytics, presented in Figure 4.

Figure 4. Key features of HR analytics. (Based on Saramies & Törnroos, 2021).

The first feature, *evidence-based*, means that HR analytics is an evidence-based method to approach decision-making. HR analytics aims to reduce the impact of cognitive biases on decision-making or relying on intuition alone -a characterization that has been traditionally linked to HR decision-making (Chalutz 2019, 1429; Dahlbom et al. 2020, 134, 135; Ghatak 2022, 5, 232; King 2016, 490; Murphy & Zandvakili 2000, 94; Rasmussen & Ulrich 2015, 236; Saramies & Törnroos 33-34). Although intuition has its place in decision-making, HR analytics aims to produce evidence-based information to guarantee reliable and justified decisions (Ghatak 2022, 78; Saramies & Törnroos 2021, 33-34).

Second feature, *diverse and multidisciplinary*, states that HR analytics consists not only of understanding and the competence in the HR function itself, but multiple other disciplines as well. Disciplines such as management, organizational psychology, statistics, organization's business operations, IT, technology solutions and especially analytics, are all involved. (Angrave, Charlwood, Kirkpatrick, Lawrence & Stuart 2016, 3; Davenport, Harris & Saphiro 2010, 55; Margherita 2022, 4; Marler & Boudreau 2017, 20; Saramies & Törnroos 2021, 34; Shet, Poddar, Wamba & Dwivedi 2021, 312) While this feature allows a comprehensive approach with the possibility to find linkages between HR data and organizational performance, it also appears to be one of the key challenges hindering the adoption of HR analytics (Dahlbom et al. 2020, 127; Ghatak 2022, 232).

The feature of *versatile use of different methods and technologies* means that to gain the maximal benefit from analytics, it is important to utilize different methods and technologies to develop reporting capabilities from basic reporting into more advanced analytics, i.e. to diagnostic or even predictive or prescriptive analytics (Saramies & Törnroos 2021, 34; Shet et al. 2021, 312, 314) Also, different analytics projects require different methods and techniques (Coron 2022, 1395-1396), hence being able to utilize a varying range of methods and techniques in order to gain insights from data is definitely an advantage for an organization.

Fourth feature, *wide possibilities of influence*, highlights the opportunity to produce significant competitive advantage and increase organizational performance through HR analytics (Saramies & Törnroos 2021, 34-35). Gaining competitive advantage is probably the most advocated benefit to promote the adoption HR analytics more widely (Bassi 2012, 15; Bonilla-Chaves & Palos-Sánchez 2023, 1; Davenport et al. 2010, 54; Ghatak 2022, 7; Marler & Boudreau 2017, 17; Minbaeva 2017, 709; Shet et al. 2021, 320).

The final feature, *more than just a system project*, points out that HR analytics and managing with HR data is not a single project, but a continuously evolving journey (Saramies & Törnroos 2021, 104-105). The technical groundwork of HR analytics is formed through information systems, data architecture, and combining of data sources. The organizational strategy creates the base for the culture of management with HR data, and only this culture forms the groundwork for evidence-based decision-making and management that is practically implemented and the results of which are communicated in organizations. (Saramies & Törnroos 2021, 35, Shet et al. 2021, 314, 319)

2.4 Organizational requirements for HR analytics

The organizational requirements for successful adoption of HR analytics form certain key concepts across the publications concerning the phenomenon presented in Figure 5. The most frequently cited concept is having *relevant skills to perform HR analytics* (Angrave et al. 2016, 1, 4, 8-9; Bassi 2012, 17; Dahlbom et al. 2020, 127; Davenport et al. 2010, 55; Lawler et al. 2004, 34; Marler & Boudreau 2017, 18; Minbaeva 2017, 703; Rasmussen & Ulrich 2015, 238-239; Saramies & Törnroos 2021, 85-87; Shet et al. 2021, 312, 317, 320; Wang et al. 2024, 7). This concept includes both HR professionals having the required analytical, mathematical, and technological skills as well as analytics professionals having the relevant knowledge in HR, if HR analytics is conducted by them. In addition to this, it is vital that there exists the ability to ask the correct questions, i.e., address relevant challenges that significantly affect the organizational performance (Angrave et al. 2016, 4-5; Dahlbom et al. 2020, 128; Huselid 2018, 680; Lawler et al. 2004, 29; Rasmussen & Ulrich 2015, 236-238). Mattson (2018, 24) compresses the relevant skills into four types of expertise: content, data, analytics and influencing expertise.

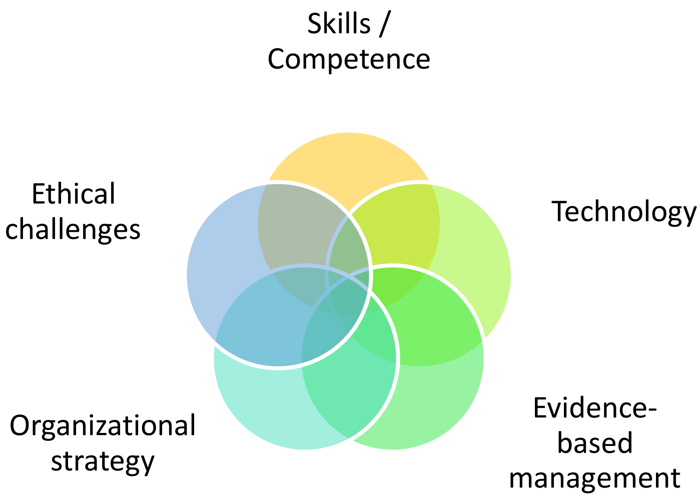

Figure 5. Organizational requirements for successful adoption of HR analytics.

Another concept that is frequently cited in the literature is *technology*. This concept can be divided into sub-concepts including HR technology and its requirements as well as several factors related with data. The HR technology requirements includes aspects such as having the technology and HR information system as an enabler of HR analytics (Lawler et al. 2004, 34; Margherita 2022 6, 9; Marler & Boudreau 2017, 20; McCartney & Fu 2022, 38-39; Saramies & Törnroos 2021, 79; Wang et al. 2024, 6), the HR information system (HRIS) having statistical functionalities to perform analyses relevant to problem solving (Angrave et al. 2016, 5, 8-9; King 2016, 491; Saramies & Törnroos 2021, 79), usability of systems and well-established IT infrastructure (Shet et al. 2021, 314, 317, 320). Aspects related to data concern data quality, privacy, and governance as well as accessibility and combining data from different departments of an organization (Angrave et al. 2016, 3-5; Dahlbom et al.

2020, 128; Davenport et al. 2010, 55; King 2016, 489-490; Marler & Boudreau 2017, 20, 22; Minbaeva 2017, 702; Rasmussen & Ulrich 2015, 237, 239; Saramies & Törnroos 2021, 117, 130-133, 150-160; Shet et al. 2021, 316-319; Wang et al. 2024, 8).

Already raised earlier in this thesis as a key feature of HR analytics, is *evidence-based management* culture. This key feature is also one of the required concepts in adopting HR analytics cited frequently (Bassi 2021, 16; Dahlbom et al. 2020, 127, 132; McCartney & Fu 2022, 39; Minbaeva 2017, 704; Saramies & Törnroos 2021, 59-63; Shet et al. 2021, 319-320; Wang et al. 2024, 9). This ability to act based on data and insights provided by it, is closely related to the *organizational strategy* concept, and should be included within it (Saramies & Törnroos 2021, 75-77). In addition to strategic ability to act, organizational strategy covers also transforming the role and focus of HR into more strategic one (Dahlbom et al. 2020, 131; Dulebohn & Johnson 2013, 72; Ghatak 2022, 225; Lawler et al. 2004, 28-29, 33; Rasmussen & Ulrich 2015, 237; Sen & Haque 2016, 184; Shet et al. 2021, 312). All aforementioned concepts are achieved through gaining *managerial buy-in* and therefore securing required resources and investments (King 2016, 490, 494; Marler & Boudreau 2017, 18-19; McCartney & Fu 2022, 28; Minbaeva 2017, 704-705; Rasmussen & Ulrich 2015, 238; Shet et al. 2021, 317; Wang et al. 2024, 8).

Finally, there is the crucial concept that relates with *ethical challenges* that needs to be taken into consideration. While analytics itself is not good or bad by its nature, the way it is used dictates which it is characterized by (King 2016, 17; Saramies & Törnroos 2021, 191). By ensuring sufficient knowledge and understanding in HR analytics, the biggest threats such as making biased decisions and violating the legal rights of employees can be avoided (Dahlbom et al. 2020, 135; Huselid 2018, 683; Wang et al. 2024, 9).

2.5 HR analytics project phases

Even though HR analytics should be viewed as a continuous journey instead of a single project that solves all organizational challenges, the single projects are parts that form that journey (Saramies & Törnroos 2021, 104-105). From a typical HR analytics project, it is possible to identify different phases, the number and exact form of which depends on the source. A summary of project phases suggested by Mattson (2018) and van Vulpen, Academy to Innovative HR (2024) is presented in Figure 6.

Figure 6. HR analytics process. (Based on Mattson 2018 & van Vulpen 2024).

Since the core idea of HR analytics is to utilize HR data to affect organizational performance, every HR analytics project should always start with an *organizational challenge* and stating the question that needs to be solved by it (Angrave et al. 2016, 9; Huselid 2018, 683; Mattson 2018, 24; Rasmussen & Ulrich 2015, 238; Saramies & Törnroos 2021, 98; van Vulpen, Academy to Innovative HR 2024). In forming this question, it is important to identify to which organizational performance metrics the result affects, which are the challenges that add most value to the organization and start by solving the most valuable or critical challenges first (Fitz-enz 2009, 3; Rasmussen & Ulrich 2015, 238; Saramies & Törnroos 2021, 99-102). The question presented forms the research question or states the hypotheses that is tested in a single HR analytics project.

According to Mattson (2018, 24) and van Vulpen (Academy to Innovative HR 2024), the second phase in the project is *identifying the data* that is needed to answer the question presented before, and where to find this data. Nowadays having the necessary amount of data is not an issue anymore, but the quality of data (Pillai & Sivathanu 2022, 3023), finding the correct challenges where to use it and having the data that is needed to solve the critical challenges, are (Saramies & Törnroos 2021, 114, 126). Some typical data resources for HR analytics projects can be for example data from recruiting or learning processes, employee surveys and performance management, i.e. internal HR data. Data from these sources can then be linked with data from different departments of the organization such as sales or finance to form valuable insights. (Coron 2022, 1394; Dulebohn & Johnson 2013, 74; Salvadorinho et al 2022, 491; Saramies & Törnroos 2021, 132-133; van Vulpen, Academy to Innovative HR 2024) In addition to internal data, also external data sources dealing with either HR or non-HR data, can be used in suitable analytics projects (Coron 2022, 1398; Salvadorinho et al 2022, 491).

Third phase, *data analysis*, begins with cleaning and processing the data. This is crucial for the quality of the insights provided by the analysis, hence the old saying “garbage in, garbage out”, which means that with low-quality, incorrect, or irrelevant data also the insights gained will be lacking and distorted. (Gabcanova 2012, 119; McEntire, Dailey, Osburn & Mumford 2006, 319; Saramies & Törnroos 2021, 117, 125; Tootell, Blackler, Toulson & Dewe 2009, 378; van Vulpen, Academy to Innovative HR 2024) After this, the actual data analysis part can be conducted. As a part of this process, the correct method and tool to solve the challenge is chosen (Mattson 2018, 24; Saramies & Törnroos 2021, 179-180). The chosen method is used to reveal possible trends, patterns, and correlations in the data. The results of this analysis are the conclusions that the data can provide to answer the question presented in the beginning of the project. (van Vulpen, Academy to Innovative HR 2024)

The phase of *actionable insights* consists of interpreting the results produced by data analysis and transforming the insights obtained from them into action (Mattson 2018, 24; van Vulpen, Academy to Innovative HR 2024). This phase is the key step of any analytics project, since in evidence-based management culture the results of analytics must lead into actions. Therefore, whether the results of an analytics project lead into action or not, is one aspect in defining if the project itself has been successful. In addition to acting based on the results, also communicating the results and their implications on the organization and its employees should be considered to have significant importance. (Marler & Boudreau 2017, 22; McEntire et al 2006, 311-312; Nienaber & Sewdass 2016, 6; Saramies & Törnroos 2021, 242-243; Tootell et al 2009, 385)

The final phase in HR analytics project is the *follow up* phase. In this phase the results of the HR analytics project are monitored to determine the impact and effectiveness of the actions taken (Coron 2022, 1396; Dulebohn & Johnson 2013, 73; Gabcanova 2012, 127; Mattson 2018, 24; Sen & Haque 2016, 177). Based on the results of these follow up measurements, it is possible to reflect and execute improvements if necessary (Saramies & Törnroos 2021, 105-106; Tootell et al 2009, 377; van Vulpen, Academy to Innovative HR 2024).

2.6 Evolution of HR analytics

According to Green (2021) the evolution of HR analytics can be divided into five sections presented in Figure 7. The first section, *age of discovery (1910-2010)*, reaches as far as to

1911 and to Frederick Taylor's Principles of Scientific Management. In his principles, Taylor connected employee measurement into optimization, efficiency, and productivity of work tasks and therefore also into organizational performance (Coron 2022, 1386; Green, A History of People Analytics in Five Ages 2021). These principles dealt on optimization on a very concrete level, aiming to maximize the productivity of each employee act through measurement. The industrial organizational psychology, nowadays still used in sophisticated people analytics functions, was another significant invention born in this age and was caused by mass industrialisation. (Green, A History of People Analytics in Five Ages 2021)

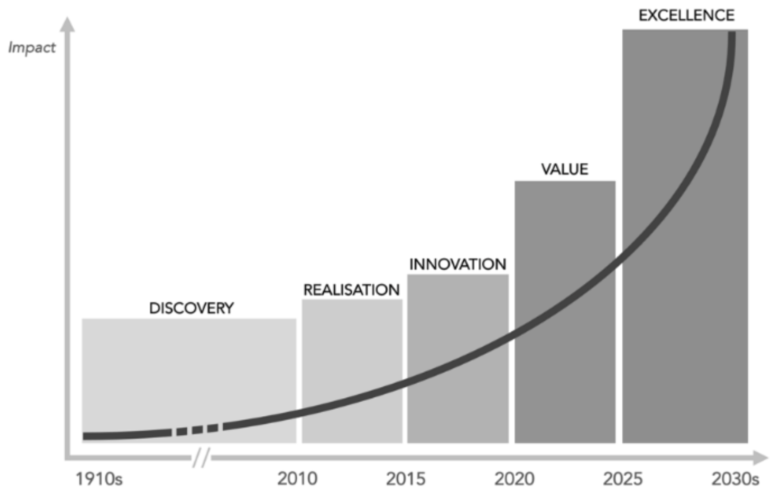

Figure 7. Five Ages of People Analytics. (Source: Green, A History of People Analytics in Five Ages 2021).

Arriving to the 1980s and 1990s, it was time for HR to extend its role in the form of taking over the responsibilities of new functions such as recruitment and development processes (Green, A History of People Analytics in Five Ages 2021). This caused the need of efficiency measurement of the HR functions itself and produced the first definitions for basic HR metrics (Bassi, 2012, 15; Green, A History of People Analytics in Five Ages 2021). For example, a pioneering article of Jac Fitz-enz (1978) highlights the importance of quantitative employee measurement as a way of securing HR a more recognized position in the managements' eyes (Fitz-enz 1978, 193, 195). However, as discussed by Green (2021), by the end of the age of discovery in 2010, the state of HR analytics functions was still highly administrative and understaffed, consisting mostly of performing activities such as annual employee engagement surveys.

Although having roots in the beginning of the 20th century, only during *the age of realisation (2010-2015)* did the full potential of HR analytics be discovered (Saramies & Törnroos 2021, 297). This was due to the global financial crisis in 2008 and companies realizing the critical role that analytics played in business. During this period, some business world giants like Google and Starbucks really invested into developing their competence in analysing the employee data to gain competitive advantage. (Green, A History of People Analytics in Five Ages 2021). This age also saw the utilization of more complex analysing techniques enabled by the dawn of big data, as well as linking HR data with data from various business actions both inside and outside the company (Bassi 2012, 15; Green, A History of People Analytics in Five Ages 2021). While famous projects like Google's Project Oxygen moved to more sophisticated analytics and thus provided some serious advantages, this age was also the time of polarization leaving some companies stuck in the descriptive analytics level and some scholars questioning the mere existence of HR analytics (Angrave et al. 2016, 1; Green, A History of People Analytics in Five Ages 2021; Minbaeva 2017, 701; Rasmussen & Ulrich 2015, 236).

Finally, in *the age of innovation (2015-2020)*, HR analytics started gaining footing in the organizational strategy and becoming a more common component of larger companies. During this age, HR analytics also became a buzz word, as it was featured in several publications as one of the most important rising trends. For example, it was ranked as the joint most important trend of the Deloitte's Human Capital Trends Report in 2018. (Green, A History of People Analytics in Five Ages 2021) In Finland, according to Saramies and Törnroos (2021), we are somewhere between the ages of realisation and innovation. This might be due to Finland's habit of procrastination in adoption of the newest technological solutions. However, this might also offer Finnish companies some advantages in the form of being able to acquire more ready-to-use technologies as well as recognizing the competence and development targets inside the company. Thus, quickening the pace in getting to the state of producing added value. (Saramies & Törnroos 2021, 299)

What is happening right now and will happen between 2020 and 2030, according to Green (2021), are *the ages of value (2020-2025) and excellence (2025-2030)*. In the beginning of this timeframe, in 2020, the global adoption of HR analytics was accelerated by three extended crises, the global Covid-pandemic, racial inequality, and financial uncertainty. Globally, the age of value has led to companies increasingly investing in their HR analytics teams and technology despite the aforementioned crises, securing HR analytics a spot in delivering direct value to the business. The global expectation for the age of excellence is for companies to fully accept and harness HR analytics. This would mean gaining the massive benefits of revenue growth currently still tied to HR data. (Green, A History of People Analytics in Five Ages 2021)

2.7 Analytics maturity levels

There are four, or depending on the source, three commonly recognized levels of maturity in HR analytics (Fitz-enz 2009, 5-6; King 2016, 488; Margherita 2022, 3; Saramies & Törnroos 2021, 176). In Figure 8, these levels are presented as Saramies & Törnroos (2021, 178) and Boatman, Academy to Innovative HR (2022), present them, adopting the framework of four different levels. Differing from this, for example, Fitz-enz (2009, 5-6) defines descriptive analytics having features of both descriptive and diagnostic analytics as well as prescriptive analytics as a combination of predictive and prescriptive analytics. Additionally, Fitz-enz presents the final level, causation, as a synthesis of descriptive and prescriptive analytics. (Fitz-enz 2009, 6)

Figure 8. Levels of analytics maturity. (Based on Boatman, Academy to Innovative HR 2022 and Saramies & Törnroos 2021).

These levels are usually presented from bottom to top, or from descriptive analytics to prescriptive analytics, indicating the level of sophistication used in the sense that the higher the level, the more advanced analytics it includes (Margherita 2022, 3; Saramies & Törnroos 2021, 177). Even though theoretically this is the case, it should be noted that organizations benefit from understanding and utilizing different types of analytics from all the levels in different forms (Boatman, Academy to Innovative HR 2022; Margherita 2022, 3; Saramies & Törnroos 2021, 179). Thus, Saramies & Törnroos (2021, 179) suggest seeing the levels as pieces of puzzle complementing each other rather than a rigid scale, each having their own cases where they are best used in. This thesis uses the framework presented by Saramies & Törnroos 2021 and Boatman, Academy to Innovative HR 2022, as it complies the commonly used levels of analytics (Banerjee, Bandyopadhyay & Acharya 2013, 1) and is more commonly used representation.

Descriptive analytics, or decision analytics, answers the question “What has happened?” and is usually labelled as the simplest form of analytics (Boatman, Academy to Innovative HR 2022). It provides information using different measures about the historical and current state of the phenomenon under examination (Fitz-enz 2009, 5; Pillai & Sivathanu 2022, 3017). A typical outcome of a descriptive analytics process is a dashboard including different metrics on various organizational processes. Analytics belonging to this level are usually used in organizations on a day-to-day basis. (Banerjee et al. 2013, 2; King 2016, 488; Saramies & Törnroos 2021, 181) For example in the aspect of HR, the traditional efficiency metrics belong to this category (Boatman, Academy to Innovative HR 2022). These metrics can nowadays be automated through various BI-solutions available, freeing up resources for more complex tasks (Dulebohn & Johnson 2013, 76-78; Saramies & Törnroos 2021, 181). The greatest advantage of descriptive analytics is that it is both simple to perform and to understand since it is based on basic mathematical skills. On the other hand, this results also into the limitations dictated by the simplicity. (Boatman, Academy to Innovative HR 2022)

Diagnostic analytics adds to descriptive analytics by answering the question “Why it happened?” aiming to reveal the underlying patterns, trends, or relationships in the data. While utilizing the same historical data as descriptive analytics, it refines the views produced from it by transforming them into valuable insights. An example of diagnostic analytics from HR’s point of view, is how employee absenteeism and overtime hours are related (Boatman, Academy to Innovative HR 2022; Saramies & Törnroos 2021, 185), i.e., are they correlated and if yes, what is the direction of the correlation. The take on diagnostics data is more exploratory in its nature, and therefore requires more from the implementation and executor, for example being able to form relevant assumptions of relationships to be tested with various techniques. (Banerjee et al. 2013, 2) Similar to descriptive analytics, also diagnostic analytics is capable of offering only static information about past occurrences (Boatman, Academy to Innovative HR 2022; Saramies & Törnroos 2021, 184). Therefore, both descriptive and diagnostic analytics levels require more from the human executor in order to be used in decision-making or to make assumptions about future (Saramies & Törnroos 2021, 180, 184).

Predictive analytics transforms historical data insights into forecasts of possible future outcomes by answering the question “What will happen in the future?” (Dulebohn & Johnson 2013, 79-80; Boatman, Academy to Innovative HR 2022; Pillai & Sivathanu 2022, 3017). It builds on top of patterns and trends revealed by diagnostic analytics by developing a model aiming to predict the future (Boatman, Academy to Innovative HR 2022; Fitz-enz 2009, 5-6; Saramies & Törnroos 2021, 186), for example through regression analysis, classification methods or clustering (Chalutz 2019, 1439; Gacia-Arroyo & Osca 2021, 4344). An example of predictive analytics use case in the HR field is using it in recruitment processes to determine and recognize desired skills and features in applicants. The availability of big data has made using predictive analytics possible since analytics belonging to this level require large amounts of relevant data to produce reliable results. (Boatman, Academy to Innovative HR 2022; Garcia-Arroyo & Osca 2021, 4346-4347) Using predictive analytics can help reduce human bias by making more informative, evidence-based decisions, and it also transforms the role of human in the analytics process from an active participant into an evaluator of the predictions produced (Saramies & Törnroos 2021, 186) producing also savings in costs at the same time (Garcia-Arroyo & Osca 2021, 4346).

The most sophisticated and complex level of analytics is called *prescriptive analytics*. The analytics tools belonging to this level not only produce future predictions, but also give recommendations on how the desired effects can be realized or how to prevent some undesired effects from happening. Thus, it answers to the question “How can it be made to (not) happen?”. (Boatman, Academy to Innovative HR 2022; Saramies & Törnroos 2021,

189) Prescriptive analytics is also often called optimization, since it allows planning, for example the use of resources, in a way that goes beyond human capabilities, being able to consider multiple internal and external variables and limitations simultaneously (Saramies & Törnroos 2021, 190). Like predictive analytics, prescriptive analytics is made possible by big data. While it reduces the work having to be done by human even further, and can even make decisions on its own, it also requires supervision since the quality of the recommendations depends on data quality. (Boatman, Academy to Innovative HR 2022) Thus, the outcomes need to be carefully assessed and validated to ensure not only their quality, but also to remove possible presence of bias included in the data while developing the tool in question (Saramies & Törnroos 2021, 189).

2.8 HR analytics vs. HR metrics

HR analytics and HR metrics are sometimes used interchangeably (Saramies & Törnroos 2021, 32). This might partly result from the incoherent terminology used of HR analytics and partly due to the ambiguity present in the literature (Marler & Boudreau, 2017, 14). Also, as discussed in the previous chapter, the analytics used with HR metrics represent one of the analytics maturity levels, and can therefore be seen as one level of HR analytics or as variables used in more sophisticated approaches of it (Garcia-Arroyo & Osca 2021, 4344). The key differences between HR metrics and HR analytics are presented in Figure 9. Whereas the traditional HR metrics are in fact a set of operational metrics describing the effectiveness of functions of HR itself, HR analytics is an advanced method to analyse HR data, and to gather it together from multiple sources (Saramies & Törnroos 2021, 32). This results also in the multidisciplinary nature of HR analytics, also discussed earlier in this thesis.

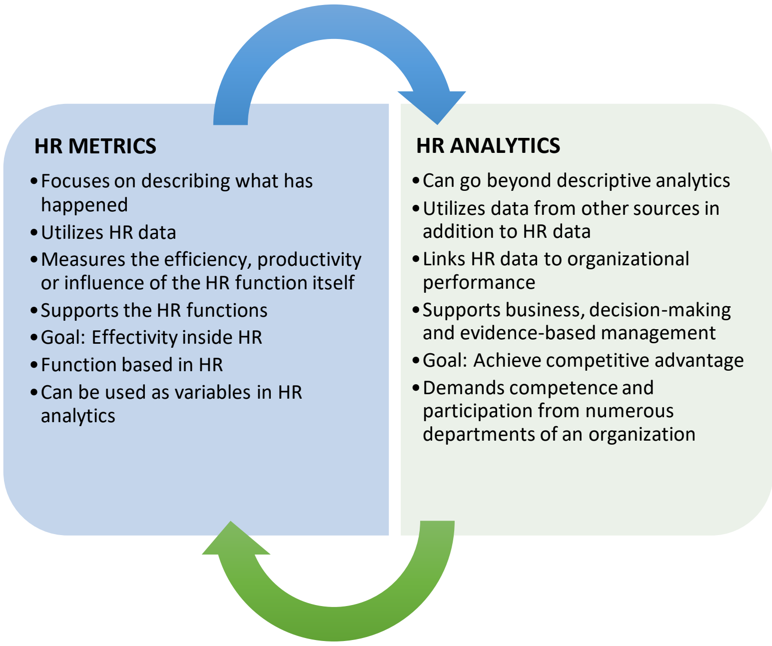

Figure 9. Key differences between HR metrics and HR analytics. (Based on Saramies & Törnroos 2021).

Lawler et al. (2004), cited by Marler & Boudreau (2017), define the main difference between HR analytics and metrics by the outcome they produce. While HR metrics produce relevant and descriptive historical data on HR operations themselves, they are often static and offer no information for management and decision-making (Lawler et al. 2004, 33; Saramies & Törnroos 2021, 68). Huselid (2018, 680) compresses the essence of HR metrics into the question "What do we need to measure about our workforce?". HR analytics, on the other hand, utilizes statistical techniques and exploratory approaches which focuses on inspecting the impacts of HR practices on organizational performance areas which they are directed on (Jiang & Akdere 2022, 190; Lawler et al. 2004, 33). HR analytics also makes it possible to form linkages between investments in talent through business processes and resources to strategic performance and illustrate the effect of these investments (Lawler et al. 2004, 33). This is described by Huselid (2018, 680) as "How do we manage and improve the metrics we deem to be critical for business success?"

3 Literature review

The literature review part of this thesis focuses on earlier research conducted on the use of quantification in HRM with the focus on HR metrics and/or analytics in the financial industry. The literature review aims to identify research that is able to answer the following questions,

- which HR metrics and KPIs are relevant in the financial industry
- what other HRM quantification approaches there are
- how can these metrics and KPIs be used in developing HR analytics solutions
- what kind of HR analytics solutions exist in the financial industry

This chapter is divided into eight subchapters starting from describing how the literature search process was conducted, which key words and search queries were formed, used and the justifications for choosing them as well as how the literature used in the review was selected. An overview on the research on HR analytics in the financial industry is also discussed. Finally, the synthesis of literature is presented in the form of discussing the key concepts discovered from the selected literature followed by a brief summary of the literature review.

3.1 Literature search process

The literature search process, which is presented in full in Figure 10, was conducted utilizing three databases, EBSCO, ScienceDirect and LUT Primo. This decision was made to ensure comprehensive coverage of relevant, high-quality literature. The two first mentioned databases were deemed reputable sources of quality research publications by the author of this thesis. The last one, LUT Primo, was additionally used to identify contributions not available through EBSCO or ScienceDirect. During the literature selection process, the following restrictions were used: written in English, peer-reviewed, academic, or scientific publications and publications available online. In addition to this, full-length articles were favoured. These limitations were set to ensure the articles used in the literature review to be of high quality and scientific in nature in addition to providing comprehensive overview of the topic.

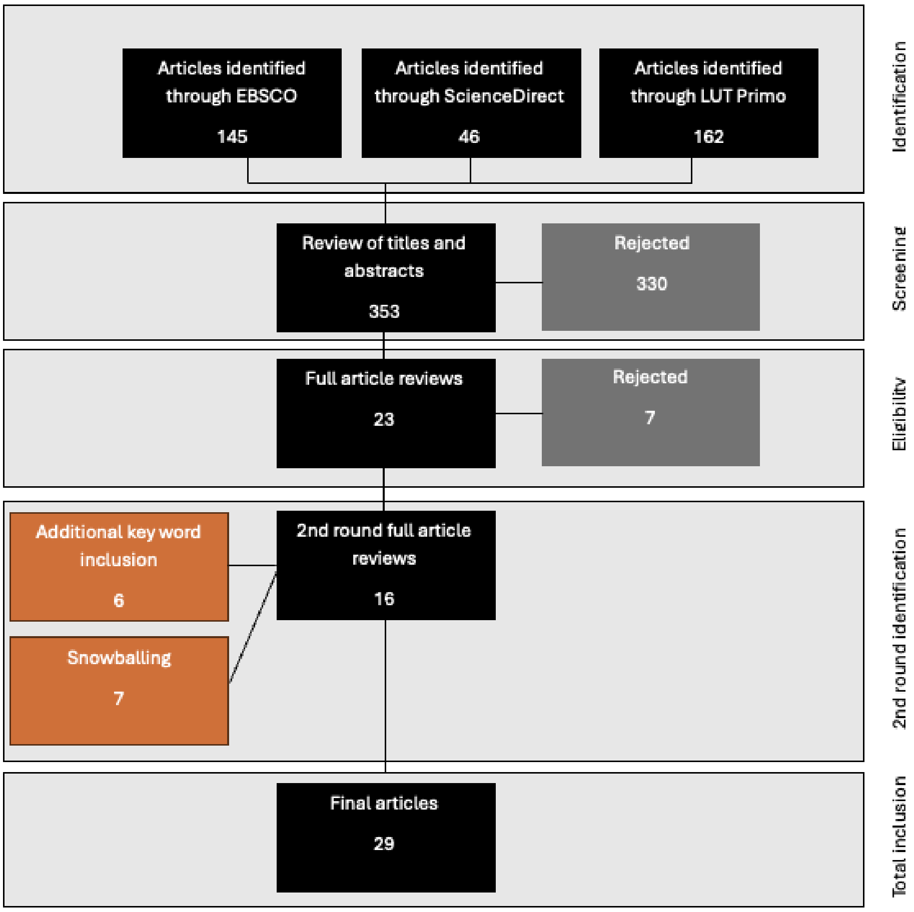

Figure 10. The literature search process.

In the beginning of the keyword identification process, the seven most frequently used search words based on the overview conducted with Google Trends by Tursunbayeva et al (2018), were utilized as a starting point. Since the practical aim of this thesis is to evaluate the state of the use of HR analytics and HR metrics in the case company, these aspects were necessary to be included in the search query. Finally, the search query was completed with the case company's industry. Therefore, the first search query was formed as,

"hr analytics" or "people analytics" or "human capital analytics" or "workforce analytics" or "talent analytics" or "human resource analytics" or "employee analytics"

and "metrics" or "kpi" or "kpis" or "key performance indicator" or "key performance indicators" and "banking industry" or "banking sector" or "banks" or "financial institution" or "financial sector" or "financial industry" or "capital markets".

With the first search query, EBSCO returned two and Primo one irrelevant result, and ScienceDirect none. With the removal of the industry part of the query, EBSCO gave 31 results with five relevant ones, ScienceDirect one result which was relevant, and Primo 42 results with four relevant ones (all amongst the ones found from EBSCO and ScienceDirect already). Several iterations of search queries were formed to ensure the inclusion of relevant literature. This part included the expansion of the scope of the industry into a more general level, which proved necessary since there seemed to be only a few articles on quantification in HRM and HR metrics and/or analytics written specifically with the scope of the financial industry. Therefore, the first part of the query was transformed into *"human resources"* or *"hr"*, and the industry part of the query was modified to include research from knowledge-intensive organizations in addition to financial industry. This decision was based on the notion that the financial industry shares some significant characteristics with knowledge-intensive organizations. These organizations are highly definable by the contribution of employees to the organizational performance and the close relation with customers with the intention of creating value for them (Jääskeläinen & Laihonen 2013, 351-352). Thus, they were seen as suitable characterizations of the financial industry. Financial industry was also included in the empirical research by Tapasco-Alzate, Giraldo-García & Ramírez-Ramírez (2022, 3036) as a one representative of knowledge-intensive organizations.

All in all, the literature identified through the search process was merged from several different queries, all of which with results gained are presented in full in appendices section of this thesis, namely in Appendix 1-3.

3.2 Literature selection process

The relevancy of the articles was primarily decided based on scanning the title and the abstract. In some indistinct cases also the introductory and conclusive parts were read through to make the decision. After the primary search process, 23 articles were chosen for closer inspection, 17 of which from EBSCO, one from ScienceDirect and five from LUT Primo.

The actual literature selection process began by scanning through all the articles in whole to make sure they were indeed relevant to the literature review and scientific in nature. Next, the articles were read, and their key concepts, methodologies and contributions were defined utilizing content analysis. During this process seven articles, which were either irrelevant or the content of which was deemed not relevant enough to the topic, were deleted. Also, the results included some articles published before the year 2000, which were decided to be removed due to the rapid development of the topic. The remaining 16 articles were read again more closely while, in addition, brief notes from each were taken to form the frame for the review together with the key concepts. This phase also contained identifying possibly significant key words not identified before from articles to include them into the search. Through this process, *"hr scorecard"* and *"human capital metrics"* were identified as key words cited by several articles and thus, another search was conducted utilizing them. This resulted into six new articles added, three from EBSCO and three from LUT Primo. In addition to this, also the snowballing technique was used to identify possible major contributions to the topic and/or contributions deemed relevant by the author of this thesis from references of the selected articles, this resulted in the addition of seven articles. All in all, 29 articles were chosen to be used as references for the literature review.

3.3 HR analytics in the financial industry

Even though the interest in the research of HR analytics has grown significantly since 2017, as presented in Figure 11 based on the research by Bonilla-Chaves & Pálos-Sanchez (2023), it has not yet specialized in individual industries. Indeed, based on the literature research process conducted, there seems to be notably little scientific research addressing the topic of HR analytics, or use of quantification in HRM altogether, with the scope of the financial industry. This probably results from two contributing factors. First, in the case of HR analytics, the phenomenon is still fairly new and majority of scientific research available is conducted on general level (Chalutz 2019, 1430, 1441; Marler & Boudreau 2017, 6, 13-14), i.e., there is only little research specified on single industry level. Second, human capital, as well as quantification in HRM, are widely discussed as key contributors to competitive advantage especially within knowledge-intensive organizations (Chalutz 2019, 1429; Jääskeläinen & Laihonen 2013, 350-352; Tootell et al 2009, 377), which combined with the notably strict secrecy policies of the financial industry make significant findings and contributions valuable assets for organizations and therefore classified information. Due to these restrictions, the literature review part of this thesis discusses the key concepts on a more general level. An exception to this is the current chapter, which continues by presenting the research conducted specifically in the financial industry.

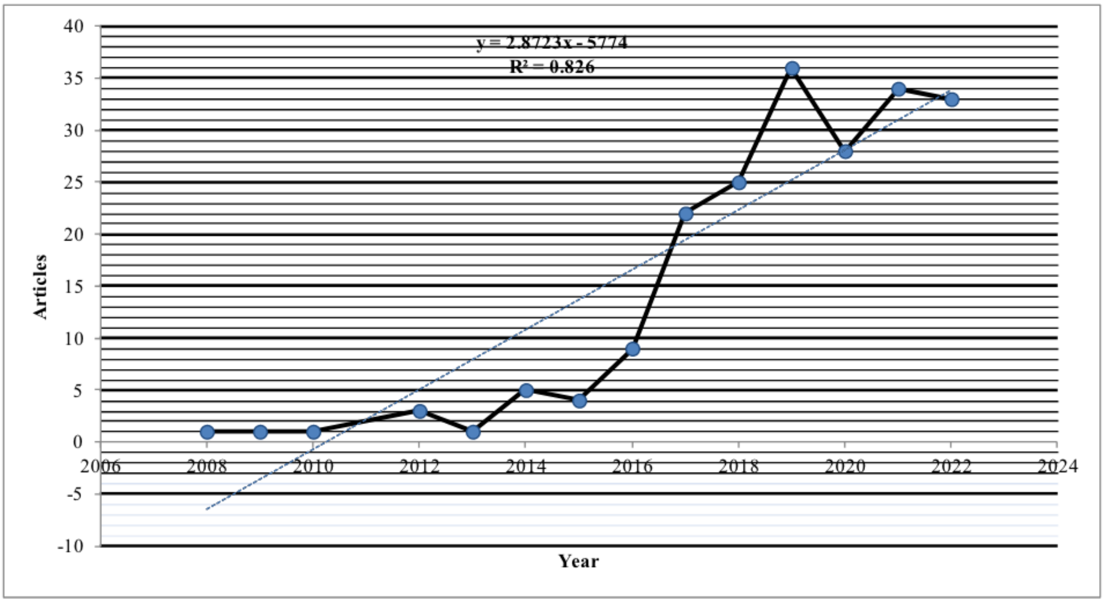

Figure 11. Annual number of scientific publications on HR analytics. (Source: Bonilla-Chaves & Pálos-Sanchez 2023)

According to Cuganesan (2006), retail banks usually tend to have similar strategic goals aiming to create value for customers through comprehensively understanding their needs resulting in sells of products and services (Cuganesan 2006, 172), which is used to assess the performance in the sales-oriented environment (Bartel 2004, 185, 188). Therefore, the differentiation must be made through outperforming competition in execution of that strategy, and HRM as well as employees are in a key position in reaching that goal (Cuganesan 2006, 172). In addition to differences in execution, also the HRM environment of the bank has been studied to affect the performance of a bank on a branch level (Bartel 2004, 201), as well as job satisfaction has been studied to have a significant negative relationship with absence (Kristensen et al 2006, 1645), which naturally affects performance negatively (Bortoluzzi, Carey, McArthur & Menassa 2018, 297). Research identified with the scope of quantification in HRM and HR metrics or HR analytics in the financial industry is presented in Table 2.

Table 2. Research on HR analytics and quantification in HRM in the financial industry.

Author	Title	Year	Analytics method	Analytics technique
Bartel, A.	Human Resource Management and Organizational Performance: Evidence from Retail Banking	2004	Econometric analysis	Regression model
Cuganesan, S.	Reporting Organisational Performance in Managing Human Resources: Intellectual Capital or Shareholder Perspectives?	2006	Qualitative data analysis	Content analysis
Kristensen, K., Jørn Juhl, H., Eskildsen, J., Nielsen, J., Frederiksen, N. & Bisgaard, C.	Determinants of Absenteeism in a Large Danish Bank	2006	Econometric analysis, predictive analytics	Reduced form equations, regression model

What is notable, is that all the research identified is empirical in its nature and two out of three studies utilize regression modelling. Also, two of the studies are focused on organizational performance, mentioning it already in the title, while also the third has concrete implications on it. In addition to these notions, it is worthwhile pointing out the geographic distribution of the studies and year of publications. While all the studies are published close together, they are geographically widely distributed with one study conducted in the United States (Bartel, 2004), one in Australia (Cuganesan, 2006) and one in Denmark (Kristensen et al, 2006). In addition to research-specific limitations discussed later, these factors should be taken into consideration while making generalizations to the Finnish financial industry.

In the study by Cuganesan (2006), the key performance indicators (KPIs) reported by the top four banks in Australia were examined through content analysis in terms of level and focus of reporting with respect to intellectual capital (IC) and corporate social responsibility (CSR) / stakeholder perspectives. The study indicated that banks reported significantly different amount of KPIs with varying focuses, the stakeholder perspective being the dominant one. This suggests that in most cases the value provided for stakeholders was seen as a more favourable approach than the value generated by human capital. (Cuganesan 2006, 179) However, it should be noted that the sample size of this study was small, posing some limitations with the generalizations of the results. The study by Bartel (2004) utilized regression analysis in studying the determinants of performance on a bank branch level specifically focusing on dimensions of a high-performance work system as characterizations of the HRM environment. The results showed that the incentives dimension of a high-performance work system had a significant positive relationship with performance on a branch level. (Bartel 2004, 201) Again, this study also has some restrictions, some of which the author has addressed by conducting visits to branch offices to provide empirical evidence to support the results of the analysis. Incentives was also identified as a driver of absenteeism in the study by Kristensen et al (2006), salary and bonus programs reducing the frequency of absence while placing limitations for salary development increased it. In their study Kristensen et al studied the determinants of absenteeism in Danske Bank by developing a regression model that utilized psychological and economic variables. Through the linear model developed, they were able to confirm the relationship between job satisfaction and absenteeism while also revealing the role of demographic factors in frequency of absences as well as the effect of managerial behaviour on the phenomenon. (Kristensen et al 2006, 1646)

3.4 Organizational performance and the role of human capital

Defined briefly, organizational performance means organization’s capability of meeting its objectives and goals (Jääskeläinen & Laihonen 2013, 351; Ismail, Nasution & Sembiring 2019, 1; Nienaber & Sewdass 2016, 5, 7). Organizational performance is widely discussed in the literature from the organizational perspective, where it is evaluated for example with a balanced view including different aspects and their linkages to strategic goals (Jääskeläinen & Laihonen 2013, 351-352) or evaluating the impact of different practices based on return on investment (ROI) (Bukowitz et al 2004, 43; Chalutz 2019, 1435; Walker & MacDonald 2001, 365). The importance of employees in ensuring organizational performance and thus competitive advantage, especially in knowledge-intensive organizations, is not new (Bukowitz, Williams & Mactas 2004, 43; Gabcanova 2012, 117; Ismail et al 2019, 1; Jääskeläinen & Laihonen 2013, 350, 352; Nienaber & Sewdass 2016, 7; Salvadorinho, Pintor, Moreira, Freire & Teixeira 2022, 489-490; Schwarz & Murphy 2008, 166; Sen & Haque 2016, 177; Walker & MacDonald 2001, 365). Therefore, when discussing the performance of knowledge-intensive organizations, and the measurement of it, the perspective of employee performance is significant (Jääskeläinen & Laihonen 2013, 352). However, the measurement of performance in this sense is problematic, since knowledge worker performance measuring usually relies on self-assessment (Bortoluzzi et al 2018, 285, 295; Jääskeläinen & Laihonen 2013, 353), which is in its nature subjective, and can thus cause issues with results and utilization of them (Jääskeläinen & Laihonen 2013, 353).

Despite this, self-assessment is still used in measuring knowledge worker performance mainly since a universal, objective solution to the problem is lacking, therefore a framework for utilizing multiple metrics is proposed by several authors (Bortoluzzi et al 2018, 295; Breunig & Hydle 2013, 570; Tapasco-Alzate et al 2022, 3050) one of them suggesting different measures for short- and long-term value creation (Breunig & Hydle 2013, 559, 578-579).

Another aspect that is defined as a characterizing attribute of knowledge-intensive organizations is the close interaction of employees and customers and the business objective of creating value for customers. Therefore, this perspective should also be taken into consideration while measuring the organizational performance of knowledge-intensive organizations. As with knowledge worker performance measurement, the measurement of this perspective poses some significant challenges since service outcomes are intangibles as well. The most significant challenges involve the difficulty of comprehensively expressing all the aspects of the service delivered as well as expressing the value created from the customer point of view. Usually, these challenges are solved similarly to knowledge worker performance measurement, i.e. using customer satisfactory surveys. In literature, only a few other solutions are suggested, for example assessing the value created for the customer through evaluating the changes in customer's turnover in business-to-business cases or using customer-oriented performance measurement or customer value-based pricing. (Jääskeläinen & Laihonen 2013, 352-354, 360)

3.5 Human resource management and the organizational role of HR

Human resource management (HRM) is defined as utilizing employees with knowledge and competence relevant to specific task to achieve organizational performance (Nienaber & Sewdass 2016, 5). Therefore, HRM practices should be aligned with the organizational strategy (Beatty, Huselid & Schneier 2003, 110, 113; Dugelova & Strenitzerova 2015, 66; Murphy & Zandvakili 2000, 94-95; Schwarz & Murphy 2008, 171; Sen & Haque 2016, 178). Even though the link between HRM practices and organizational performance has been established by multiple studies (Bartel 2004, 183), the direction of the relationship and causality between HRM practices and organizational financial performance remains still unproven (Chhinzer & Ghatehorde 2009, 42-43; Sen & Haque 2016, 178). Even when this is the case, changes in organization's financial performance are often reflected in HRM practices concerning headcount of an organization (Chhinzer & Ghatehorde 2009, 37; Dugelova & Strenitzerova 2015, 64; Sen & Haque 2016, 178).

The fourth industrial revolution has created new challenges with HRM (Salvadorinho et al 2022, 488, 490). These challenges include changing working conditions due to globalization, employee mobility and technological aspects as well as the availability of employees with relevant skillsets such as analytical and technical skills (Breunig & Hydle 2013, 560; Chalutz 2019, 1429; Garcia-Arroyo & Osca 2021, 4343; Nienaber & Sewdass 2016, 6; Salvadorinho et al 2022, 489-490; Sen & Haque 2016, 177). Also, the process of measuring human capital, which still lacks the much-needed conceptual transparency, poses challenges for management even today (Nienaber & Sewdass 2016, 6). In addition, the increase in the amount of data available not only sets new analytical possibilities, more efficient HRM practices and higher quality decision-making (Garcia-Arroyo & Osca 2021, 4338), but also requirements for employee competency and HRM practices (Salvadorinho et al 2022, 490, 495).

Originally, the role of HR department has been focusing on operative, administrative tasks (Beatty et al 2003, 107; Dulebohn & Johnson 2013, 72; Fitz-enz 2009, 1). While other departments of an organization have been more agile in developing their technical and analytical skills and procedures, HR department is in the situation where it faces multiple threats if it is not able to prove its value. Such threats comprise inability to ensure sufficient resources invested in HR practices (Bukowitz et al 2004, 43; Dugelova & Strenitzerova 2015, 64; Murphy & Zandvakili 2000, 94), outsourcing or even total exclusion from the organization (Beatty et al 2003, 107; Fitz-enz 2009, 1-2; Sen & Haque 2016, 177; Tootell et al 2009, 379). In addition to this, the increasing role of employees in securing organizational performance in modern organizations (Beatty et al 2003, 107; Cuganesan 2006, 166-167; Sen & Haque 2016, 184), there is an undeniable need for HR to take a more strategic role in the organization (Dulebohn & Johnson 2013, 72; Sen & Haque 2016, 184). This offers HR department the possibility to become a significant business partner and team up with other departments. To reach this goal, the adoption of measurement and analytics, a data- and metrics-driven approach (Murphy & Zandvakili 2000, 95-96; Schwarz & Murphy 2008, 168), i.e., evidence-based decision-making, is in critical role (Beatty et al 2003, 107; Dulebohn & Johnson 2013, 73-74). Especially the use of higher-level analytics helps with strategical HRM decision-making and can result in enhancing organizational performance (Coron 2022, 1396; Pillai & Sivathanu 2022, 3012, 3021-3022).

3.6 Technical aspects

Inside organizations, varying data formats and amount of data available for analysing purposes today, so called big data, pose challenges in the technical aspect for data collection and storage (Garcia-Arroyo & Osca 2021, 4343; McEntire et al 2006, 312, 321), measurement and development of analytical solutions (Garcia-Arroyo & Osca 2021, 4345; McEntire et al 2006 321; Salvadorinho et al 2022, 490) as well as ethical questions (Garcia-Arroyo & Osca 2021, 4344-4345). Therefore, decisions regarding what data to collect, how and how long data is stored (Garcia-Arroyo & Osca 2021, 4343; McEntire et al 2006, 311; Pillai & Sivathanu 2022, 3016), how to ensure sufficient data quality (Marler & Boudreau 2017, 22; Pillai & Sivathanu 2022, 3009, 3016-3017), how the data is processed and analysed (Garcia-Arroyo & Osca 2021, 4343-4345; Melnyk, Stewart & Swink 2004, 211), and how the privacy issues involved with data are solved (Garcia-Arroyo & Osca 2021, 4345), are more important than before. However, the era of big data also presents organizations with new possibilities of utilizing their data (Garcia-Arroyo & Osca 2021, 4337, 4354), especially in knowledge-intensive organizations where employees are in a key role in generating organizational performance. According to research by Garcia-Arroyo & Osca (2021), in the HRM context the contributions of big data can be classified into five main groups, HR research and practice, selection and hiring, assessment and development, information, learning and knowledge and strategic, efficiency and performance.

3.6.1 Data sources

According to Coron (2022) and Salvadorinho et al (2022) there are four types of data sources related with HRM practices; 1) *internal HR data*, 2) *external HR data*, 3) *internal non-HR data* and 4) *external non-HR data*. The selection of which source(s) are used depends on the practice that is taken (Coron 2022, 1398). *Internal HR data* comprises from employee related data gathered and stored by the organization itself, and it includes data such as employee surveys and employee demographical data (Chalutz 2019, 1440; Coron 2022, 1394;

Salvadorinho et al 2022, 491). It is utilized in basic HRM practices (Coron 2022, 1394) such as establishing training needs and determining employee engagement and performance. *External HR data* contains information on employees from sources outside the organization, platforms such as Facebook or LinkedIn, and it can be utilized for example in recruitment and selection practices (Coron 2022, 1398; Garcia-Arroyo & Osca 2021, 4346) or in conducting employee sentiment analysis (Nienaber & Sewdass 2016, 15). *Internal non-HR data* sources include data from other departments inside the organization such as finance (Chalutz 2019, 1440; Coron 2022, 1394; Salvadorinho et al 2022, 491), and it can be used for example in HR scorecard approach, which includes other organizational perspectives in addition to HR (Coron 20221, 1398). *External non-HR data* covers, e.g., publicly available databases (Coron 2022, 1394-1395; Salvadorinho et al 2022, 491), and it can be used for example in benchmarking purposes (Coron 2022, 1395).

3.6.2 Analytics methods

It is possible to classify analytics methods in more than one way. These classifications can be made for example based on analytics purpose, data form, or method. The classification based on purpose of analytics includes similar classes, or levels, as the analytics maturity levels presented earlier in this thesis. This classification, which is used for example in studies conducted by Chalutz (2019), Fitz-enz (2009), Melnyk et al (2004), Nienaber & Sewdass (2016) and Pillai & Sivathanu (2022), makes the division into descriptive and predictive analytics and is the most common classification used.

However, Garcia-Arroyo & Osca (2021) present a deviating classification using the classification based on analytical method approach, presenting the methods in four groups: 1*) text analysis*, 2) *multimedia analysis*, 3) *supervised learning* and 4) *unsupervised learning*. Like the name indicates, *text analysis* is used to analyse data that is in text form. Usually, one of the three main techniques, word count analysis, common characteristics extraction or co-occurrence of words, is used based on whether data is structured or not. Both common characteristics extraction and co-occurrence of words utilize algorithms in identifying patterns in data or sequences of words. (Garcia-Arroyo & Osca 2021, 4344) These types of analytics can be used for example with employee sentiment analysis extracting employee view on certain HRM practices (Nienaber & Sewdass 2016, 15) or in classification of employee talent (Chalutz 2019, 1440). *Multimedia analysis* helps in analysing data in various forms, namely in sound, picture and video formats. Like with text analysis, also here identification of common patterns is used through utilizing data mining techniques to gain valuable information. *Supervised and unsupervised learning* models represent the main techniques used in data mining and machine-learning. While both aim to learn from the data provided, supervised learning utilizes independent and dependent variables and the relationships between them to make predictions about future observations mainly through classification, regression or evaluation of models. (Garcia-Arroyo & Osca 2021, 4344) Examples of this type of analytics are studying the determinants of absenteeism (Kristensen et al 2006) or predicting the probability of success of new recruitments (Chalutz 2019, 1440). Unsupervised learning, on the other hand, aims to capture and express patterns in the data without using dependent variables, e.g. through utilizing cluster analysis (Garcia-Arroyo & Osca 2021, 4344).

3.7 Quantification in the HRM context

Unlike HR analytics, using quantification in HRM is not a new phenomenon. Several research with the scope of using quantification in HRM have been made. In recent years, also systematic literature reviews aiming to capture the essential contributions to the topic have been published (Coron 2022, 1387), as well as listings of frameworks and techniques used to measure human capital (Gabcanova 2012, 117). While quantification itself is a broader term (Coron 2022, 1386), the literature review part of this thesis mainly focuses on the use of metrics and analytics presenting different approaches of using them in the HRM context.

According to Melnyk et al (2004, 211) measurement is a verifiable process expressed in quantitative or qualitative terms with respect to a reference point. Metrics apply the use of mathematical formulas or algorithms (Fitz-enz 2009, 1; McEntire et al 2006, 313), and they offer a universally understood way of communicating quantifiable aspects of activities and practices and their contribution to organizational performance (Breunig & Hydle 2013, 578; Dulebohn & Johnson 2013, 73; Pillai & Sivathanu 2022, 3022; Tootell et al 2009, 375, 378) with an aim to help in decision making (McEntire et al 2006, 310; Melnyk et al 2004, 211).

What comes to organization's departments measuring their activities, HR is often seen as one of the most lagging departments inside the organization with measurement development and practices (Beatty et al 2003, 108; McEntire et al 2006, 310-311; Murphy & Zandvakili 2000, 94; Tootell et al 2009, 376). This is explained to result from the characteristics of HR department dealing with "soft" business, and human capital related issues being challenging to measure in quantifiable terms unlike metrics of many other departments (Bukowitz et al 2004, 43; Dulebohn & Johnson 2013, 74; Tootell et al 2009, 376-377, 379) as well as HR department's lack of analytical skills, confidence in using metrics (Chhinzer & Ghatehorde 2009, 38; McEntire et al 2006, 312) and the thought process of a business partner (Fitz-enz 2009, 2; Schwarz & Murphy 2008, 170). However, through appropriate measuring it is possible to highlight the contribution of HRM practices to organizational performance (Coron 2022, 1396; Dulebohn & Johnson 2013, 73; Sen & Haque 2016, 177), as presented in Figure 12 based on the conceptual model by Pillai & Sivathanu (2022).

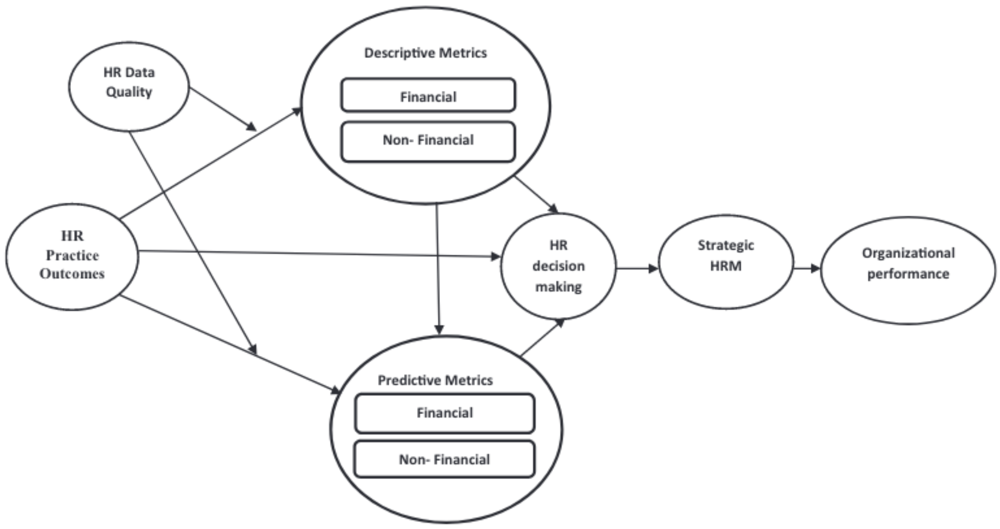

Figure 12. Conceptual model for deriving organizational performance from HR practices. (Source: Pillai & Sivathanu 2022)

In addition to demonstrating the value of HRM practices, measurement also allows for management, taking corrective actions when necessary and assessing the effect of decisions made (Coron 2022, 1396; Dugelova & Strenitzerova 2015, 64; Nienaber & Sewdass 2016, 6; Tootell et al 2009, 377), providing justification for allocation of resources (Fitz-enz 2009, 4-5; Murphy & Zandvakili 2000, 94, 97; Schwarz & Murphy 2008, 165), conducting benchmarking (Dugelova & Strenitzerova 2015, 64), acquiring a more comprehensive understanding of the situation of the organization's workforce (McEntire et al 2006, 319) and finally, initializing the development of HR analytics (Fitz-enz 2009, 1). Here, the highlight is on word *appropriate,* since inappropriate measures or missing aspects may result in incorrect outcomes and thus flawed decisions and behaviour (Gabcanova 2012, 119; McEntire et al 2006, 319; Tootell et al 2009, 378). Therefore, it can be said that the quality of decisions made are only as good as the knowledge gained from measuring used (Nienaber & Sewdass 2016, 6) and the quality of the data, which acts as a moderating factor (Pillai & Sivathanu 2022, 3023).

3.7.1 HR metrics and human capital metrics

HR metrics and human capital metrics are similar concepts, but their focus is slightly different. While HR metrics are defined as measurements of the HR function itself (Marler & Boudreau 2017, 14; Nienaber & Sewdass 2016, 10-11; Pillai & Sivathanu 2022, 3010; Sen & Haque 2016, 177), human capital metrics measure the activities and competences of employees and their effect on the organizational performance (Cuganesan 2006, 166; Nienaber & Sewdass 2016, 10-11), i.e. the value of human capital (Dulebohn & Johnson 2013, 74). This literature review discusses both aforementioned under the same heading using the unified term HR metrics, since human capital metrics is sometimes seen as one level of HR metrics (Dulebohn & Johnson 2013, 74), and they can, and should, be both used within HR analytics.

According to Fitz-enz (2009) everything in an organization is measurable using five different ways: cost, time, quantity, quality, and human reaction (Fitz-enz 2009, 3). The decision what to measure and which HR metrics are the most appropriate and relevant ones for the organization depends on several aspects, such as strategy, vision, and industry of the organization (Chhinzer & Ghatehorde 2009, 45; Dugelova & Strenitzerova 2015, 66). Since measuring itself is a practice, it also requires resources. Therefore, measurement should be applied primarily to HR metrics dealing with organizational problems which create the highest value and impact organizational performance the most (Fitz-enz 2009, 3), and the link how the measured HR practice creates value for the target group, external or internal, should be defined (Melnyk et al 2004, 211).

HR Metrics can be classified in multiple different ways. Classification can be done by the type of data source into *quantitative* and *qualitative* metrics (Bortoluzzi et al 2018, 283), or *leading/predictive* and *lagging/descriptive* ones depending on the effect the HR practices have on organization (Gabcanova 2012, 125), or into *financial* and *non-financial* metrics (Melnyk et al 2004, 212; Pillai & Sivathanu 2022, 3011) depending on the focus of the HR metrics.

Quantitative metrics, as the term suggests, use measurable data while *qualitative* metrics utilize data that is not measurable. Even though this is the case, also qualitative metrics can provide a numeric outcome through analytics process. Bortoluzzi et al (2018) present a unique metric utilizing both types of data sources, the resulting metric being thus called a *mixed* one. (Bortoluzzi et al 2018, 286, 288-289) *Leading* metrics are also called *predictive* metrics, since they use a higher level of analytics, and can hence impact future HRM practices (Gabcanova 2012, 125; Pillai & Sivathanu 2022, 3010, 3024) or aim to improve the chances of a certain goal to be reached (Melnyk et al 2004, 212). However, commonly the HR metrics used in organizations are *lagging*, or *descriptive* ones, conveying information about the outcomes of HR practices that have already happened, i.e. which are not possible to be managed anymore (Gabcanova 2012, 125; Melnyk et al 2004, 212; Pillai & Sivathanu 2022, 3010, 3024). The terms descriptive and predictive stem from maturity levels of analytics, describing the corresponding level of analytics used with each metric. *Financial* metrics focuses on metrics that have impact on financial performance of an organization, such as cost per employee (Bortoluzzi et al 2018, 294; Melnyk et al 2004, 212). *Non-financial* metrics, on the other hand, measure practices that affect the organizational performance in other aspects than financial, such as employee engagement score (Melnyk et al 2004, 212; Pillai & Sivathanu 2022, 3011-3012).

The overall HR performance balance can be assessed for example conducting gap analysis, i.e. comparing the balance between the performance measurements of different metrics (Ismail et al 2019, 6). Even though financial and quantitative metrics are more common than qualitative and non-financial metrics, the importance of qualitative and non-financial metrics is beginning to gain footing in HR decision-making and strategic HRM (Pillai & Sivathanu 2022, 3017; Tootell et al 2009, 390). All in all, best outcomes from using metrics can be derived from developing a set of metrics covering the whole range of classifications (Pillai & Sivathanu 2022, 3022-3023). Still, there are some differences in the frequencies of use of performance metrics between literature and practical perspectives (Melnyk et al 2004, 210; Tapasco-Alzate et al 2022, 3040), indicating the different interests between academics and managers (Melnyk et al 2004, 210).

In addition to classifications of metrics, HR metrics are generally divided into different levels. These three levels are: 1) *efficiency,* 2) *effectiveness* and 3) *impact* metrics (Dulebohn & Johnson 2013, 73-74; Marler & Boudreau 2017, 14; Pillai & Sivathanu 2022, 3011). *Efficiency* metrics are the most popular metrics used in the HR context since they focus on measuring the performance level of HR with the most basic practices. Also, these metrics focus on easily quantifiable aspects, namely profits and costs, and they are therefore easily understood. *Effectiveness* metrics, like the name suggests, measure the effect HR practices have on target group or function. Through these metrics it is possible to identify effective and ineffective practices, as well as gain information on features that define an effective practice. Thus, effectiveness metrics are also called cost-benefit metrics. *Impact* metrics, on the other hand, are the most important ones in communicating the value of HR since they measure the impact of HR practices on organizational performance (Dulebohn & Johnson 2013, 73-74; Pillai & Sivathanu 2022, 3011). These metrics include combining data from other departments of an organization in addition to HR data and utilize more sophisticated techniques to reveal relationships between HR practices and organizational performance. (Dulebohn & Johnson 2013, 73-74)

The challenges identified with developing and utilizing metrics can be roughly divided into three aspects, 1) *development process,* 2) *acceptance* and 3) *operalization of measures* (Chhinzer & Ghatehorde 2009, 38; Tootell et al 2009, 381). The challenges associated with *development of measures* result from the lack of knowledge of HR practices and skills in designing, selecting appropriate metrics and in analytics, as well as identifying the impact of the metrics selected (Chhinzer & Ghtahorde 2009, 38; Garcia-Arroyo & Osca 2021, 4356; Marler & Boudreau 2017, 18-19; McEntire et al 2006, 312-315; Tootell et al 2009, 383). Issues with *acceptance* result from low level of managerial buy-in, organisational history and structure, HR's role, the importance associated with the measurement action deemed by the shareholders (Chhinzer & Ghatehorde 2009, 38; Marler & Boudreau 2017, 19; Tootell et al 2009, 384), as well as the lack of conceptual transparency (Nienaber & Sewdass 2016,

6) and validity of metrics (Chhinzer & Ghatehorde 2009, 38; McEntire et al 2006, 318). Challenges with *operalization* result from technological aspects, lack of resources, low level of communication of the results, poor utilization of the information gained or from slowness of the analytics process conducted (Marler & Boudreau 2017, 20, 22; McEntire et al 2006, 311; Nienaber & Sewdass 2016, 6; Tootel et al 2009, 385).

3.7.2 HR key performance indicators

Key performance indicators (KPIs) represent measures of performance in reaching specific organizational goals (Cuganesan 2006, 168; Gabcanova 2012, 127; Salvadorinho et al 2022, 490). KPIs measure the specific organizational practices that are the most critical ones to organizational performance (Breunig & Hydle 2013, 570; Gabcanova 2012, 119-120), or issues the organization aims to develop (Cuganesan 2006, 168; Sen & Haque 2016, 178), i.e., they are the most important metrics, hence the name key performance indicators. HR KPIs are the most used approach of evaluating the performance of HRM practices (Dugelova & Strenitzerova 2015, 64; Dulebohn & Johnson 2013, 73). The selection of relevant KPIs has a significant meaning and should therefore be thoroughly thought through during the development process to choose KPIs that align with the organizational strategy (Cuganesan 2006, 168; Gabcanova 2012, 127). From HR point of view, this requires understanding the impact HRM activities have on organizational performance (Cuganesan 2006, 168; Gabcanova 2012, 127; Schwarz & Murphy 2008, 170). However, HR performance cannot be expressed using a single, all-inclusive KPI (Sen & Haque 2016, 178; Tootell et al 2009, 376). Thus, in literature, multiple KPIs are presented as beneficial to measure as well as multiple frameworks and processes how to select the appropriate ones for specific organization, such as framework for knowledge worker productivity by Bortoluzzi et al (2018, 297), and triangulation of methods by Salvadorinho et al (2022, 492).

In addition to being relevant, some key aspects recognized with effective KPIs are clear, simple enough, actionable, reachable, measurable (Gabcanova 2012, 119, 121), and credible to the target audience (Tootell et al 2009, 380). KPIs should also be changeable in case of changes in the organizational strategy (Dugelova & Strenitzerova 2015, 73), which can cause problems since KPIs should also be comparable over time (Melnyk et al 2004, 211). The difference between a KPI and a contributing factor should also be taken into consideration.

While KPIs are dependent on changes in their contributing factors, making them dependent variables, factors themselves are independent. Sometimes the differentiation between these two concepts is not clear enough, and they are used interchangeably. (Bortoluzzi et al 2018, 282, 292)

3.7.3 HR scorecard

HR scorecard is an approach of linking HRM practices and employees to organizational performance (Beatty et al 2003, 109; Gabcanova 2012, 117; Marler & Boudreau 2017, 16; Schwarz & Murphy 2008, 171), thus it is focused on strategic goals of an organization (Beatty et al 2003, 109; Ismail et al 2019, 1; Nienaber & Sewdass 2016, 11; Schwarz & Murphy 2008, 172; Walker & MacDonald 2001, 368) and view HR as a strategic asset. HR scorecard, developed by Becker, Huselid & Ulrich in 2001 (Gabcanova 2012, 117; Schwarz & Murphy 2008, 172), is an HR focused variation of the balanced scorecard (Gabcanova 2012, 121; Walker & MacDonald 2001, 368). The balanced scorecard was originally presented by Kaplan and Norton in 1996, and the first version of it was amongst the earliest approaches of addressing both tangibles and intangibles. With relation to HR and employees, intangibles are viewed as knowledge, processes, and innovation (Tootell et al 2009, 377-378; Walker & MacDonald 2001, 368).

The original balanced scorecard approach utilizes four perspectives 1) financial, 2) customer, 3) internal/business process and 4) learning and growth, and organization’s KPIs should be set to cover all these perspectives, thus linking HRM practices to strategic goals (Gabcanova 2012, 118, 122). Gabcanova (2012), presents a framework illustrating how the linkage can be developed, which is presented in a simplified manner in Figure 13. After defining strategic goals, the strategy map is developed including all the four perspectives of the HR scorecard with the definition of partial goals. The supportive HR practices are also defined to reach the partial goals, and the development and changes in these goals are followed through KPIs. (Gabcanova 2012, 122, 125)

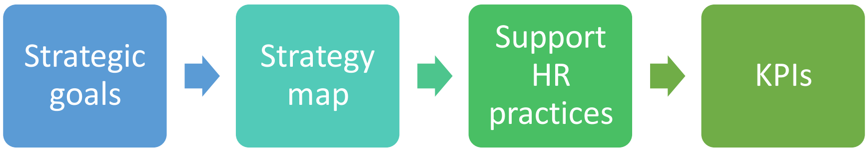

Figure 13. Linking HRM practices to organizational strategic goals. (Based on Gabcanova 2012)

While HR Scorecard usually utilizes the same four perspectives, in some frameworks subtle alternations may be suggested. However, usually also these frameworks include the financial and customer perspectives (Walker & MacDonald 2001, 368), since financial performance is deemed to ultimately be the most critical measure of organizational success, while employees, especially in the knowledge-intensive organizations, work in close relation with customers (Gabcanova 2012, 119, 121; Jääskeläinen & Laihonen 2013, 352-353). Some frameworks also suggest linking HR scorecard with business scorecard (Beatty et al 2003, 116-117), or take the HR scorecard development even further, incorporating it with other decision-making techniques such as Analytical Hierarchical Process (AHP) to assess the performance (Ismail et al 2019, 2).

When discussing HR scorecard, it should be noted that according to the articles included in this literature review and their references, some major contributions of this subject are published in book form and are therefore out of the scope of this review.

3.7.4 HR accounting

The theoretical framework and practices of human resource accounting (HRA) are contributions of several authors building on work started by Hermanson in 1964 and represents yet another approach of communicating the value HRM practices create for organizational performance (Tootell et al 2009, 377). HRA aims to measure the human capital and HR practices purely in financial terms using costing and utility models as tools to transform the value generated into more understandable and commonly used form for managers and shareholders (Schwarz & Murphy 2008, 166; Tootell et al 2009, 377). One general, supporting argument for the adoption of HRA is that organizations get more value from employees than the amount that is invested in them in the form of salaries (Bukowitz et al 2004, 44; Cuganesan 2006, 165; Schwarz & Murphy 2008, 166). However, measuring employees as assets does not come without difficulties since the human element and knowledge cannot be expressed comprehensively in accounting terms (Bukowitz et al 2004, 44; Tootell et al 2009, 377).

3.8 Summary of the literature review

The literature review part of this thesis has discussed research identified with the scope of use of quantification in the HRM context and HR analytics as well as the main concepts within them. Like stated earlier, the main finding of this review is the fact that research conducted with the aforementioned scope in the financial industry is scarce. Hence, the scope of literature used in this review was expanded to include literature from knowledge-intensive organizations which were deemed to be to some extent comparable with the financial industry through their similar special characteristics.

While HR analytics is still a new, emerging concept (Chalutz 2019, 1430, 1441; Marler & Boudreau 2017, 6), using quantification in HRM is not (Coron 2022, 1386). This conclusion can also be derived from the literature, e.g. from the history of the use of quantification in HRM, publication years of articles discussing different approaches of quantification in HRM as well as approaches such as treating HR metrics as one level of HR analytics or as variables used in developing it (Garcia-Arroyo & Osca 2022, 4338, 4344). In Table 3 the literature used in the review is presented in a matrix form stating the key concepts recognized and utilized in constructing this review.

Table 3. Concept matrix for literature used in the review.

	Year	Concept										
Author		hr analytics in the financial industry	organizational performance	HRM	technical aspects	data sources	analytics methods	quantification in HRM	HR metrics	HR KPIs	HR scorecard	HRA
Murphy & Zandvakili	2000			x				x				
Walker & MacDonald	2001		x					x			x	
Beatty et al	2003			x				x			x	
Bartel, A.	2004	x		x				x				
Bukowitz et al	2004		x	x				x				x
Melnyk et al	2004				x			x	x	x		
Cuganesan	2006	x		x				x	x	x		x
Kristensen et al	2006	x					x	x				
McEntire et al	2006				x			x	x			
Schwarz & Murphy	2008		x	x				x		x	x	x
Chhinzer & Ghatehorde	2009			x				x	x			
Fitz-enz	2009			x				x	x			
Tootell et al	2009			x				x	x	x	x	x
Gabcanova	2012		x					x	x	x	x	
Breunig & Hydle	2013		x	x				x		x		
Dulebohn & Johnson	2013			x				x	x	x		
Jääskeläinen & Laihonen	2013		x					x				
Dugelova & Strenitzerova	2015			x				x	x			
Nienaber & Sewdass	2016		x	x				x	x		x	
Sen & Haque	2016		x	x				x	x	x		
Marler & Boudreau	2017				x			x	x			
Bortoluzzi et al	2018		x					x	x	x		
Chalutz	2019		x	x		x	x	x				
Ismail et al	2019		x					x	x		x	
Garcia-Arroyo & Osca	2021			x	x	x	x	x				
Coron	2022			x		x		x				
Pillai & Sivathanu	2022			x	x			x	x			
Salvadorinho et al	2022		x	x	x	x		x		x		
Tapasco-Alzate et al	2022		x					x	x			

HR metrics and HR KPIs are the most familiar approaches of quantification in HRM (Dugelova & Strenitzerova 2015, 64; Dulebohn & Johnson 2013, 73), and they have been the subject of multiple studies. This fact coincides with the frequency of approaches identified in the matrix with 16 articles discussing HR metrics and 10 articles HR KPIs. Since KPIs are special cases of metrics, the result is quite clear. However, despite the notable amount of research, significant challenges regarding development, acceptance and operalization of metrics remain.

In addition to HR metrics, this review has briefly discussed other approaches of implementing quantification in the HRM context. Approaches such as HR scorecard and HRA have also been developed to demonstrate the value of HR and human capital to organizational performance (Beatty et al 2003, 109; Gabcanova 2012, 117; Marler & Boudreau 2017, 16; Schwarz & Murphy 2008, 171; Tootell et al 2009, 377). Seven articles included within this review have been identified to discuss HR scorecard and four HRA, making them clearly less researched approaches. However, it should be again noted that according to the articles dealing with HR scorecard as well as their references, some major contributions concerning this concept are published in book form.

While all, HR metrics and KPIs, HR scorecards and HRA are used in measuring and evaluating HR practices, human capital and their contribution to organizational performance, there are some key differences between these approaches which might also explain the difference in the frequencies of appearance of these approaches in research. Whereas HR metrics focus on measuring the HR function (Marler & Boudreau 2017, 14; Nienaber & Sewdass 2016, 10-11; Pillai & Sivathanu 2022, 3010; Sen & Haque 2016, 177) and consists of individual metrics measuring one practice individually, HR scorecard offers a more comprehensive understanding of HRM practices and their contribution to overall organizational performance and goals (Beatty et al 2003, 109; Gabcanova 2012, 117; Marler & Boudreau 2017, 16; Schwarz & Murphy 2008, 171). Since HR department has traditionally been seen as an administrative function of organization (Beatty et al 2003, 107; Dulebohn & Johnson 2013, 72; Fitz-enz 2009, 1), utilizing HR metrics which are in their nature descriptive and operational seems fitting concerning this purpose. However, the changes resulting from the fourth industrial revolution (Salvadorinho et al 2022, 488, 490) and acknowledging the role of employees in generating organizational performance (Beatty et al 2003, 107; Cuganesan 2006, 166-167; Sen & Haque 2016, 184), have created pressure for transforming the role of HR into a more strategic one (Dulebohn & Johnson 2013, 72; Sen & Haque 2016, 184). This in turn has generated the need for more balanced approach of linking HR practices to organizational strategy and HR scorecard can be viewed as one attempt in transforming HR's role into a more strategic one. HRA, on the other hand, focuses on expressing human capital as an asset, adopting purely financial perspective to quantification in HRM (Schwarz & Murphy 2008, 166; Tootell et al 2009, 377).

4 Data and Methodology

In this chapter the theoretical knowledge obtained through this thesis is combined with the information gained from the semi-structured interviews about the state of the case company X, which operates in the Finnish financial industry. The key concepts discussed both in the theoretical framework and in the literature review are used to assess the current state of company X with respect to these key concepts.

The motivation for company X to develop their HR analytics stems from the strong organizational culture of evidence-based management, typical for operators in the financial industry, and the significant rise in the number of people employed by company X during the past few years. Additionally, the current state of HR reporting has been deemed to require significant amount of manual labour and to be overall very time consuming by several representatives of the company involved in HR reporting.

4.1 Research method and data collection

The research part of this thesis is qualitative case study since it was conducted through executing brief semi-structured interviews with representatives of company X from different roles. These representatives included employees concerned with HR reporting and consisted of two HR managers and two development managers. Key aspects about interviewees are presented in Table 4. While the quantitative approach including exploratory analysis could have also been an option, the circumstances during the thesis project offered the possibility of conducting the research in the form of interviews only. This resulted from the current state of the use of HR analytics in the case company, which at the temporal scope of this study was only at the beginning. Thus, the qualitative approach was deemed more suitable for examining the initial state of the case company and making general suggestions concerning the next steps of the HR analytics development project. Therefore, qualitative study was selected as a research method since the data collected from the interviews was in non-numerical form naturally guiding the selection of the research method.

Table 4. Representatives of company X participating in the interviews.

Interviewee	Role	Tenure in current role	Responsibility areas	Date interviewed
A	HR manager	2 years	HR reporting	18th of June 2024
B	HR manager	4 years	Pay and incentives, matters related with employment contracts, HR reporting during A's absence	20th of May 2024 2nd of August 2024
C	Development manager	2 years	Management and reporting of employee skills and competence	12th of June 2024
D	Development manager	2 years	Management and reporting of occupational well-being and company culture	12th of June 2024

The interviews were conducted through Teams between April and August in 2024, and they lasted approximately 45 minutes each. The timing of the research was primarily dictated by the timeliness of the thesis as well as the launching of the HR analytics development project of the case company. With B there were two interviews held since the first interview with this representative included the presentation of current reporting routine and was done before the theoretical part of the thesis was completed. Thus, some key concepts were not identified and discussed at this point of the research.

The interview questions were slightly modified depending on the role of the interviewee, but the overall frame was similar for all. The interview questions were grouped according to key concepts identified in the theoretical part of this thesis. All the interview questions are presented in the appendices of this thesis, in Appendix 4. During the interviews notes were made by the researcher to form a comprehensive understanding of the current state of the company with respect to reporting and analytics as well as the key concepts identified in the theoretical part of this thesis.

5 Case Description

5.1 Employee competence with relation to HR reporting and analytics

The person mainly responsible of HR reporting in practice, interviewee A, works in company X under the title HR manager. A has completed Master's degree in Business Administration with major in human resource management, but their educational background does not include studies in reporting or analytics besides courses taken on Excel. A's responsibility area of HR data and analytics is based on personal interests. A's working background comprises of HR practices from several years' time, and in the current role A has worked for two years. A has received internal training concerning how to run reports from the reporting service and HRIS of the company. A is very interested in developing their reporting and analytics skills further in the future.

The second interviewee, B, works also as a HR manager in company X. B has conducted HR reporting occasionally, during the absence of A. B's educational background includes Bachelor's degree in Business Administration with a major in human resources. Also B has received internal training concerning running reports from different company systems as well as advice to ad-hoc problems. What comes to developing skills in reporting and analytics, B appreciates the importance of evidence-based management and wants to stay up to date what is happening inside the company. However, as B's core competence is in matters related to with employment contracts and pay and incentives, they are not deeply interested in developing their skills in the field of analytics.

Interviewee C works as a development manager with core responsibility area in skills and competence development management. C has completed Master's level studies in Business Administration with major in evidence-based management. C is not actively part of HR reporting, but occasionally gives advice how to customize single reports to better meet the end-users needs. In the future C might participate in reporting using a competence management system since it represents their current core responsibility area. Like others, also C has received internal training concerning how to run reports from the reporting service and HRIS of the company.

The second development manager interviewed, D, has completed Master's degree in Business Administration with major in human resource management, and has worked in the current role for two years. D conducts reporting through the HRIS and occupational health care system but has also some previous reporting experience from their earlier position within the same company. D has also received internal training on using the company reporting systems. D is really interested in developing their reporting and analytical skills further since they see evidence-based management and decision-making in a significant role in the future.

In addition to the aforementioned employees, the business controller of company X has also participated in the discussion of what kind of internal non-HR data especially from the financial sector of the company could be used in HR analytics development project. Business controller has diverse experience from reporting and analytics and uses them on daily basis. Due to this experience, they are participating in developing of HR reporting and analytics. Like others, also business controller has completed Master's level in Business Administration with major in insurance and risk management. However, as they have not participated in the HR reporting and work under finance department, i.e., do not have the insight of the themes discussed, they were not interviewed for this case study.

5.2 Evidence-based management culture and managerial buy-in

According to interviewee D, the culture of evidence-based management is strong inside company X. However, they state that inside the HR department there would be some room for improvement, but the large amount of qualitative data in HR sets challenges in achieving the same level as other business functions, for example finance. Interviewee C sees that while the overall evidence-based management culture could be more organized, the current HR analytics project offers a possibility to enhance both the evidence-based management culture and the use of results in decision-making.

What comes to managerial buy-in, both C and D are satisfied with the investments and involvement the management has allocated for HR practices including the development of HR reporting and analytics. According to them, this is demonstrated in company's strategic goals as well as in the sheer existence of roles like theirs. Also, the launching of the current HR analytics project indicates the willingness of investing in developing HR reporting and analytics and interest of deriving information from data that can be used in evidence-based management and decision-making. Interviewee A also states that management is interested in developing HR reporting and analytics as well as obtaining data and information about the company workforce. According to A, the development of evidence-based management is strongly included in the company agenda. This is reflected in the increase of resources allocated to HR during the past few years states B. B also clarifies that since the reporting requests are usually made by management, the resources are more easily available than if the request was made by HR.

5.3 Organizational role of HR and strategic goals

While the organizational role of HR in company X has been more administrative, the significant rise in the number of employees during past few years has transformed the role into a more strategic one. According to C, the HR department of each company is responsible for the administrative practices of that organization, i.e., the role of HR departments is primarily administrative. Also B states that while HR's role has been transforming towards being more strategically focused, the primary role of HR will always stay administrative to some extent. In addition to individual HR departments inside organizations, X has also a central HR department which guides the HR strategy and distributes strategic material for individual organizations, i.e., has purely strategic role. However, the individual organizations have some room in executing the strategy at their own discretion due to for example different market areas.

As discussed in the research by Cuganesan (2006, 172), creating value for customers is a common strategic goal for many retail banks in Australia. This seems to be also true with Finnish banks based on an overview conducted by the author of this thesis on multiple banks' websites in addition to company X's, and the visions, values and strategies stated on them. Another similarity point in strategies between multiple Finnish banks is the goal of achieving productive and responsible operation and growth. According to Cuganesan (2006, 172), in situations where multiple companies aim to reach similar strategic goals, execution becomes the distinguishing factor between companies. This point of view is also reflected in company X's strategic goals, which are presented in Figure 14.

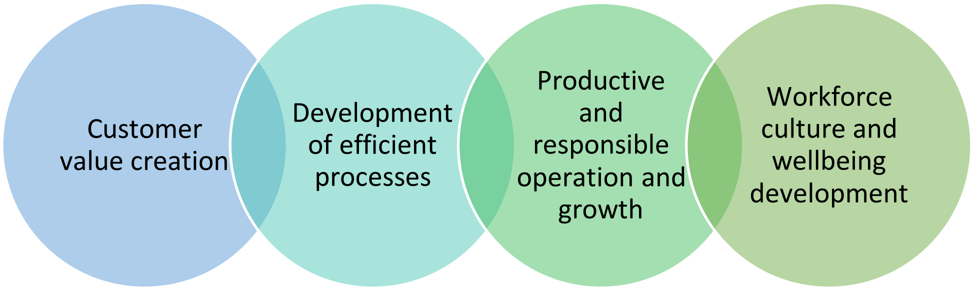

Figure 14. Strategic goals of company X.

Since companies operating in the financial industry can be seen as representatives of the knowledge-intensive organizations, the workforce, their knowledge and competence as well as the services provided by them are in the key position in creating competitive advantage (Cuganesan 2006, 172). Therefore, the employee aspect reflected in many Finnish banks' strategies, also in company X's, with an aim for developing the workforce culture and wellbeing, is not surprising.

5.4 Current state of HR reporting

The HR reporting of company X has been conducted in its present form for two years with slight alternations. Currently, this reporting includes analytics from descriptive level in the form of metrics representing events that have already happened, presented in Figure 15. These metrics are based on request by the executive team of the company. The analytics tool used for reporting the metrics is Microsoft Excel, and the metrics are visualized using basic graphs. The actual presentations for managers and executive team are prepared and presented with PowerPoint which includes the visualizations produced in Excel. The present reporting interval of company X is one month or in some cases one year. However, company X is currently developing data packages with various themes to be reported quarterly. The reporting is conducted fully manually mainly by one of the HR managers, A, and all the metrics are reported with respect to different business functions of the company.

Figure 15. Monthly reported HR metrics of company X.

First metric, the number of full- and part-time contracts includes the number of employees in both full- and part-time positions at the end of the reporting period. Second metric, full-time equivalent (FTE) expresses the number of the personnel transformed into full-time employees at the end of the reporting period. The transformation is made based on the working time stated in the employee's contract, for example the FTE of an employee with 50% working time is 0.5. The number of full- and part-time contracts is mainly utilized in comparison with FTE. Both of the aforementioned metrics are also reported compared to budgeted figures, i.e. in this case the number of employees that is budgeted for each business function for each reporting period.

Workforce mobility concerns the number of new and terminated contracts including the number of contracts terminated due to employee transferring into another position inside the same group. Turnover is reported using different codes for different exiting reasons, for example retirement and voluntary employee turnover are reported with different codes. Overtime is reported by hours, and open positions by the number of positions that are currently open in recruitment processes. The number of open positions is produced by the recruiting team and included in the PowerPoint presentation prepared by the HR manager responsible for HR reporting.

In addition to HR metrics mentioned above, company X also reports and follows the occupational well-being metrics presented in Figure 16. These metrics are reported by D, one of the development managers, to business function managers who monitor the changes in their own areas of responsibility.

Figure 16. Occupational well-being metrics of company X.

Sickness absences are reported as a number of occasions per person for one year's time interval, and the sickness absence and health rates as a rate between a group and time interval determined by the user. Diagnostic categories present information on diagnosis resulting in sickness absences on a general level, meaning that individual diagnoses are not available for the user. Both working time and over time are reported as hours and they are followed from the occupational well-being aspect. Work engagement metric is monitored as a part of weekly pulse surveys and includes a series of questions regarding the work experience using Likert (1-5) scale.

Currently, employee skills and competence are reported on annual basis. The metrics involved in this reporting are presented in Figure 17. Company X has recently invested in talent management system Y, a platform designed to help organizations in talent management. Company X expects it also to aid in developing the reporting of this aspect in the future. The interval of employee skills and competence reporting is intended to increase.

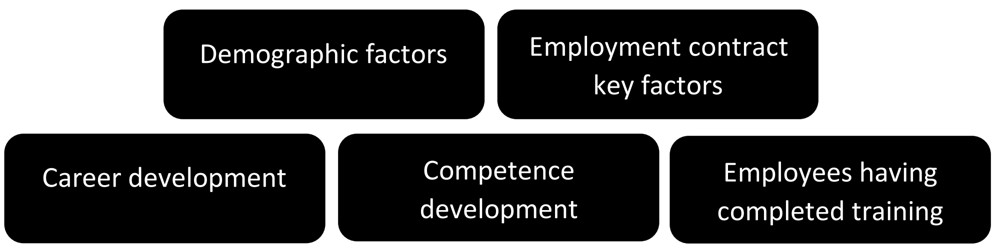

Figure 17. Company X's HR-metrics reported annually.

Career development is reported as the number of position transitions inside the company. These transitions can include transitions into different roles at different difficulty levels. Competence development is reported as hours and euros used in developing skills and competence per employee and employees having completed certain training as a total number of employees per training course. Annual reporting also includes information about workforce demographic factors and equality, emphasizing various aspects with respect to gender distribution. In addition to reporting the overall gender distribution, this dimension is monitored with respect to age distribution, different personnel groups, role difficulty level, difference in pay level and the use of parental leaves. Furthermore, having equal possibility in career and competence development and the use of partial working time are measured. Additionally, some key factors concerning employment contracts are reported as well, for example the number of new and terminated contracts. All these figures are also reported with respect to different business functions.

Furthermore, as a part of developing HR reporting and analytics, company X is developing various data packages to be reported. These packages include different themes, for example one addressing competence development and another various aspects of turnover. These data packages are intended to be reported quarterly.

In addition to presenting the aforementioned metrics, D states that answers to open questions of employee surveys are analysed either by manually identifying the key concepts or through word clouds produced by the reporting system. Utilization of word clouds poses challenges since answers often include words such as “work” which do not offer concrete value in identifying significant concepts. D also states that some piloting experiments have been conducted in the field of data analysis in the form of correlation and regression analysis between workload and work engagement. D feels that with the new system enabling the use of higher-level analytics, the challenge of identifying the correct tools to be used with each case emerges. Even though employees participating in HR reporting are interested in developing their analytical and reporting skills and have some experience in this era, the analytical and statistical experience among HR workforce is lacking creating some level of uncertainty.

5.5 Utilization of reporting results and communication of reporting goals

The results of current HR reporting are utilized in different business functions of the company in everyday management. This includes for example the use of results in concrete development practices in competence development and wellbeing, and on team level on smaller-scale decisions based on results of weekly pulse surveys. The results are also used in performance evaluation and compensation of line managers. On organizational level the results of metrics such as FTE are viewed with respect to different business functions of the company and used in decision-making concerning the number of new hires per function. The communication of the reporting results is conducted in HR info sessions, where demographic metrics such as the average age of workforce and the development of the number of employees are discussed.

According to D, the communication of the reporting goals could be better especially at the strategic level. While the company does measure activities related with strategic goals, the communication of how well these goals are met is still lacking, i.e., there could be metrics visualizing the success in reaching each individual goal. Interviewee A also states that the intended use cases of reporting results could be more clearly stated. In addition, interviewee B would like to have more open and faster feedback from the management directly to the employees conducting the reporting.

5.6 Reporting systems

In company X, HR reports are run either from the reporting service or HRIS. All the employees interviewed state that running the reports from HRIS could be generally easier and faster. According to A, some time ago there were even occasions when reports could not be run at all, and the filtering inside the system itself is very slow. Interviewees B and C state that sometimes it is difficult to find the desired report or information from HRIS. B adds that another problem with the usability and functionality with the HRIS is its stiffness. This means that the system functions based on pre-determined usage rights, i.e., to access HR data, the user must have certain rights activated. This poses challenges in co-operation between different departments since e.g. the business controller cannot directly access HR data. While this data can be provided on request, it slows down practices and makes processes such as exploratory analysis difficult since the recipient should be able to provide the HR department precise request on the data that is needed.

Having said that the reporting systems have some clear shortcomings, interviewee A states that the department responsible for the development of reporting is very receptive to development needs and provides support on low threshold. A has co-operated with the department for example in cases when the desired report must have been formed through combining several reports into one. In this case the development department has created a new report including the desired data to be run instantly by the user without the need of combining individual reports.

5.7 Data collection, privacy and quality

Company X's HR related data is collected from multiple sources. Demographic data is stored in the HRIS and originates from the employees directly. This is currently also the case with data concerning employee skills and competence, while the intention of the company is to transfer this information into talent management system Y and have the skills and competence evaluated also by the team manager. Data concerning occupational wellbeing is collected through a wellbeing survey carried out twice a year with each business function and on organizational level annually, as well as through a wider range occupational health survey conducted every two years.

Like all the operators in the financial industry, also company X has strict privacy policies concerning data management and privacy. The data management privacy and legality are regularly monitored by a data protection team. For each personnel register, including the HR register, there must be a written privacy statement describing the purpose for collecting and processing the information. These privacy statements must also inform the person whose information is processed whether they are subject to automated actions such as profiling through the register, and to describe the logic behind these actions. Additionally, the processing of all the personal information must have legal basis and these bases must also be expressed on the privacy statement. There are also some common responsibilities, such as responsibilities concerning taxation, that naturally must be followed by all the operators in the financial industry.

In company X, data quality is a common responsibility amongst the whole of workforce. This means that each employee making entries in the systems must exercise due diligence to avoid variation in the spelling form of the information. In some information input areas, there are drop-down menus that effectively prevent cases where two observations are labelled as two separate cases due to different forms of spelling, even though they should in fact be labelled as just one. The HR manager responsible for HR reporting, A, states that while these deviations in data quality mainly occur with entries including personal information and are therefore not concerned in the actual reporting outcomes, there are cases where incorrect information has resulted in flawed reporting outcomes. An example of a case like this are absence periods where either an employee his-/herself or the line manager responsible for making the entry has forgotten to update information due to a change in situation, resulting HR reporting including incorrect total number of “active” employees. Additionally, interviewee B sees problems with data quality resulting from the organizational structure inside the group. B states that individual organizations are in some cases restricted by usage rights and the system does not work well on organizational level resulting in data that is not reliable enough considering the size of company X.

5.8 Data sources

In company X, HR reporting currently utilizes solely internal HR data. The reporting of all the metrics discussed previously are based on data from either the reporting service or the HRIS of the company. The HRIS houses majority of the employee related data recorded in the company, and comprises of dimensions such as demographical factors, incentives, absence and occupational well-being. Data concerning employee competence and skills are partially stored and processed through talent management system Y, as discussed before. Since the implementation of the system has only recently been done, this resource is not yet fully utilized and data concerning this dimension as well is currently saved in the HRIS. In addition to aiding in talent management, the objective of introducing the talent management system is to acquire a more comprehensive view of employees’ skills and competence. At present, this information is expressed through entries recorded by the employees themselves and is based on their own estimate of, for example, their language skills.

While external HR data, like information from platforms such as LinkedIn, is utilized in the recruitment process, this comprises from traditional, manual work done by recruiting HR workforce. Hence, these practices do not involve higher level of analytics or use of algorithms. Neither internal nor external non-HR data is currently utilized in company X HR reporting, although it should be said that there have already been discussions in combining internal non-HR data especially from finance with internal HR data. The company has already identified this process potentially problematic since there are multiple systems used to store data and combining information from these sources most likely requires lots of work.

6 Results

This chapter begins by summarising and evaluating the situation of the case company with respect to the key concepts identified through the theoretical part with a focus on concepts directly related to analytics and reporting. Evaluating the situation with respect to each concept is complemented with some general improvement and development suggestions for company X. In addition to this, an example solution for an organizational challenge presented by the case company is discussed.

In addition to the interviews, descriptive HR report statements delivered by company X were used to determine the reporting possibilities offered by the reporting service and human resource information system (HRIS) of the company.

6.1 Employee skills and competence

In general, the initial situation of company X employees' skills with respect to reporting and the use of analytics reflects the level of analytics currently in use inside the company. Almost all the employees concerned with HR reporting have some previous experience from conducting similar or equivalent practices. Also, the employees interviewed seem genuinely interested in developing their skills further in this field at least to some extent. However, during the interviews it was also observable that while the interviewees were familiar with the level of analytics used with the current reporting practices comprising mainly of descriptive metrics and including the understanding of basic mathematical skills, more sophisticated analytical and statistical skills were clearly missing from the employees' skillset.

According to Mattson (2018, 24), there are four types of expertise needed for conducting a successful HR analytics project: *content, data, analytics and influencing expertise*, see Figure 18. The first type of expertise, *content expertise*, includes knowledge needed with almost every step of a typical HR analytics project. In company X this expertise is fulfilled moderately, since all the employees currently conducting the reporting have working history in the field of HR. Therefore, it is reasonable to assume that they are also able to identify the potential challenges occurring in HR which could be solved using analytics, creating insights from the results gained as well as conducting the follow-up measurement of progress made. What comes to identifying the correct method or tool needed to solve the challenge, employees are able to some extent fulfil this goal. This is true especially with problems that can be solved using basic analytics at the descriptive level or with identification of a method on a general level. An example of such situation was presented by one of the competence managers including the use of word clouds in recognizing significant themes in the open answers section of employee surveys. While the idea itself is useful, the execution without the exclusion of common words or so-called stop words reduces the significance of the results obtained. Thus, there is a need for deeper knowledge of the practical implementation of the tools in order to utilize them in a way that produces credible and accurate insights.

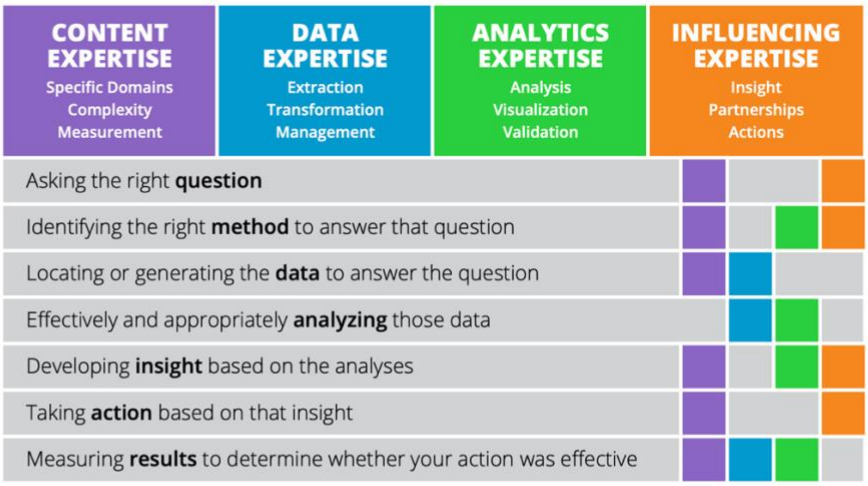

Figure 18. Types of employee expertise required in a typical HR analytics project. (Source: Mattson 2018)

As stated above, the biggest skill gaps of company X workforce seem to lie in *data and analytics expertise*. While the employees having conducted HR reporting before have some experience from analytics also, this comprises mostly of descriptive analytics run with Microsoft Excel. The future participation of the business controller brings more versatility to the data and analytics expertise through their experience especially in data extraction, transformation, analysis and visualization. The business controller has also experience from other analytics tools, e.g. from Power BI, but skills required to utilize more sophisticated analytics solutions and tools are still lacking from company X's employees' skillset. Also, company X does not have employee(s) dedicated to HR data management and data quality, thus affecting the competence level associated with the *data expertise*.

Therefore, either hiring or consulting a data analyst would probably prove beneficial for the case company concerning both data and analytics expertise. Another option would be to offer specialization training for the existing employees. With company X, this is a feasible option that can be considered since all the interviewees can be classified into learning enthusiasts. People belonging to this group are characterized as open to analytics and willing to learn but lacking the necessary skills and/or training. Since this group offers the opportunity to enhance the evidence-based management culture inside the HR department, the enthusiasm should be utilized. (Saramies & Törnroos 2021, 84) However, as training deduction is longer available for companies in 2025, the resources allocated for internal training might be affected (Veronmaksajat 2024).

When it comes to *influencing expertise*, the participation of the business controller offers HR a financial partner able to produce insights from the financial aspect as well. Naturally, the executive team also takes part in this type of expertise through making decisions based on the results of the analytics. As majority of the employees interviewed in this study stated that the executive team has showed high level of interest in developing HR reporting and analytics, the state of acting based on the insights obtained seems promising.

6.1.1 Employee performance measurement

According to research by Tapasco-Alzate et al (2022, 3036), representatives of the financial industry can be seen also as representatives of the knowledge-intensive organizations. As employees working in knowledge-intensive organizations are in key position in increasing organizational performance (Bukowitz et al 2004, 43; Gabcanova 2012, 117; Ismail et al 2019, 1; Jääskeläinen & Laihonen 2013, 350, 352; Nienaber & Sewdass 2016, 7; Salvadorinho et al 2022, 489-490; Schwarz & Murphy 2008, 166; Sen & Haque 2016, 177; Walker & MacDonald 2001, 365), the performance of employees should be measured also. Like with majority of knowledge-intensive organizations, knowledge worker performance measurement in company X is executed as subjective self-assessment (Bortoluzzi et al 2018, 285, 295; Jääskeläinen & Laihonen 2013, 353). In addition to self-assessment, the performance of each employee of company X is evaluated by line managers.

However, according to literature review conducted, a single, objective solution to this measurement problem is still lacking. Therefore, the framework of utilizing multiple metrics is proposed by multiple authors, e.g. Bortoluzzi et al (2018) and Breunig & Hydle 2013. In their research Bortoluzzi et al (2018) present a framework for measuring office worker performance through a set of four KPIs illustrated in Figure 19.

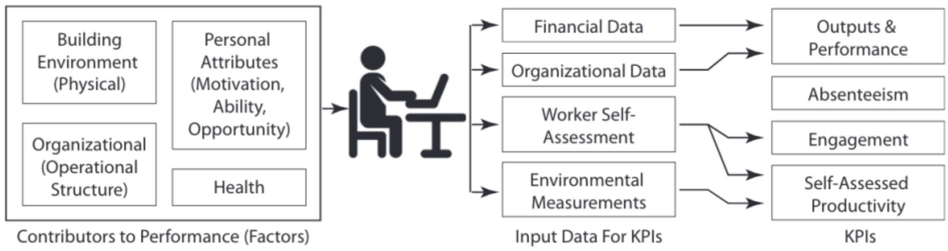

Figure 19. Framework for measuring office worker performance. (Source: Bortoluzzi et al 2018)

Since company X already measures absenteeism and engagement and utilizes self-assessment in evaluation of performance, combining information from outputs and performance, for example realized customer interactions, could prove beneficial in engineering an overall worker performance measurement solution that would at the same time be rather simple to implement.

6.2 Evidence-based management culture and the communication of results

The state of the evidence-based management culture in the case company was addressed since it was cited by multiple authors as one of the significant factors contributing to the successful adoption of HR analytics (Bassi 2021, 16; Dahlbom et al. 2020, 127, 132; McCartney & Fu 2022, 39; Minbaeva 2017, 704; Saramies & Törnroos 2021, 59-63; Shet et al. 2021, 319-320; Wang et al. 2024, 9). Again, as with data privacy, this concept was deemed to be on sufficient level with respect to the scope of this thesis. This conclusion was based on the interviews conducted in the case company which were seen as reliable views due to the case company industry and its special characteristics. As a company operating in the financial industry, it is natural for the case company to make decisions based on data.

Therefore, the implementation of this culture in the HR department as well was seen highly believable.

While discussing the communication and utilization of the reporting results, there was one significant element identified as currently missing. According to the interviews, the follow up of success in reaching the organizational goals is not reported at all. Regarding this, company should determine a scale and base values indicating to which level each goal is met. Regular measurement and visualization of these results would help employees in understanding to which extent the goals are reached and the managers on which aspects more resources and effort should be allocated to.

6.3 Analytics maturity levels, methods and tools

Currently, company X HR analytics comprises primarily of descriptive analytics in the form of metrics. These metrics are produced using the reporting service and HRIS of the company. Since performing descriptive analytics manually on daily basis is rather tedious and time-consuming (Saramies & Törnroos 2021, 181), the case company would undoubtably benefit from automating it for example using Power BI, a tool from which the business controller of the case company has experience from. Therefore, this solution would probably be the fastest and simplest for the case company to implement. Through automating the descriptive reporting, company X could free up resources for practices that have the potential to enhance organizational and financial performance. At its simplest, this can mean analysing the insights obtained from the automated reporting more efficiently and thus providing the executive team professional support from the HR domain point of view.

Besides the metrics, one of the development managers cites that some initial experiments have been made with correlation and regression analyses concerning the relationships between occupational well-being and work engagement. According to Saramies & Törnroos (2021, 179-180), utilizing methods from different analytics maturity levels provides variety to insights obtainable from analytics. Also, the decision which analytics method should be used depends primarily on the organizational challenge that is desired to be solved through analytics (Saramies & Törnroos 2021, 201). While the descriptive analytics primarily used in the case company focus on presenting the historical developments of a certain variable, diagnostic analytics utilized in experimental cases examine the relationships between variables of interest, i.e., provide insights on possible correlations. However, it should be noted that correlation does not imply causation (Brooks 2008, 28). Thus, the results obtained should be viewed carefully and before making decisions based on the insights, domain knowledge or theory should be revised to offer justification for the decision. The preliminary experiments done in company X with respect to the relationship between occupational well-being and work engagement can be seen to have similar aspects to the study by Kristensen et al (2006), since job satisfaction and work engagement are both related with employee retention. The other aspects, absenteeism and occupational well-being, can also be reasoned to both affect the employee performance. Therefore, analysing insights from the results obtained from studying the relationships between these variables has some theoretical background in the literature. Thus, making decisions based on the insights obtained is more convincingly justified. Regarding utilization of correlation analysis altogether, company X could expand the use of correlation analysis on other variables as well.

Besides correlation analysis, company X could also include regression analysis into their HR analytics methods. Considering previous research conducted in the financial industry, both Bartel (2004) and Kristensen et al (2006) have utilized multivariate regression in determining determinants of both bank performance on branch level and absenteeism. Since regression models allow making predictions about future observations as well, they would add another level to HR analytics conducted in company X. However, these models can be used only if the amount of data is sufficient. Utilization of regression analysis with an example case representing an organizational challenge of company X is discussed later in this chapter.

All in all, the level of HR analytics currently conducted in company X coincides with the notion made by Saramies & Törnroos (2021, 299) stating that Finland is currently somewhere between the realisation and innovation eras considering the HR analytics evolution. The realisation era is characterised as the era when the full potential of HR analytics and its implications on competitive advantage were discovered (Saramies & Törnroos 2021, 297), and the innovation era by HR analytics gaining a more common role within organizations (Green, A History of People Analytics in Five Ages 2021), which seems to characterize the current situation of company X quite well. The company has understood the value of HR analytics and aims to implement it to their daily routine but is only at the beginning of the journey using analytics solutions almost entirely from only one of the analytics maturity levels.

Considering analytics tools, HR reporting is currently performed using Microsoft Excel solely and the results are presented for the executive team as PowerPoint presentations. While Excel offers possibilities for implementing analytics beyond the descriptive level, for example in the form of correlation analyses from the diagnostics level, it has some downsides that can be addressed using other software designed for carrying out more sophisticated analytics. For example, R and Python are both free open-source programming languages that include multiple options for methods from all the analytics maturity levels with an option to make personalized visualizations. In addition, as both are popular data analytics tools, it is quite simple to find advice, support and solutions to problems online. These software are also capable of loading, combining and running larger datasets faster than Excel, an advantage that should not be overlooked since the amount of data available inside organizations is constantly growing.

6.4 Data sources

According to the studies by Dahlbom et al (2016, 128) and Marler & Boudreau (2017, 22), HR data accessibility pose significant challenges for organizations. With company X, already the preliminary discussions concerning this thesis revealed that one challenge in developing HR analytics is associated with the fact that data, both HR and non-HR data, is stored in multiple locations across the organization. Thus, combining data from variable sources is challenging and time consuming, therefore effecting the efficiency of decision-making processes (Wang, Liu, Lin, Sindakis & Aggarwal 2024, 1173).

On the other hand, one challenge introduced in the beginning of the HR analytics development project was to identify possible data sources to be combined with HR data to produce multidimensional and valuable insights. The theoretical part of this thesis has identified and presented the types of data used in HR analytics projects: internal HR data, internal non-HR data, external HR data and external non-HR data. Currently, company X utilizes only internal HR data in the form of demographic, recruiting, occupational well-being, skills and competence, job architecture, working time, absence and employee survey data. While the internal HR data is versatilely used, the commissioning of the other data sources introduced is one significant piece in unlocking the use of also higher-level analytics. For example, one potentially interesting combination of internal HR data combined with internal non-HR data, in this case financial and customer relationship management (CRM) data, is illustrated in Figure 20.

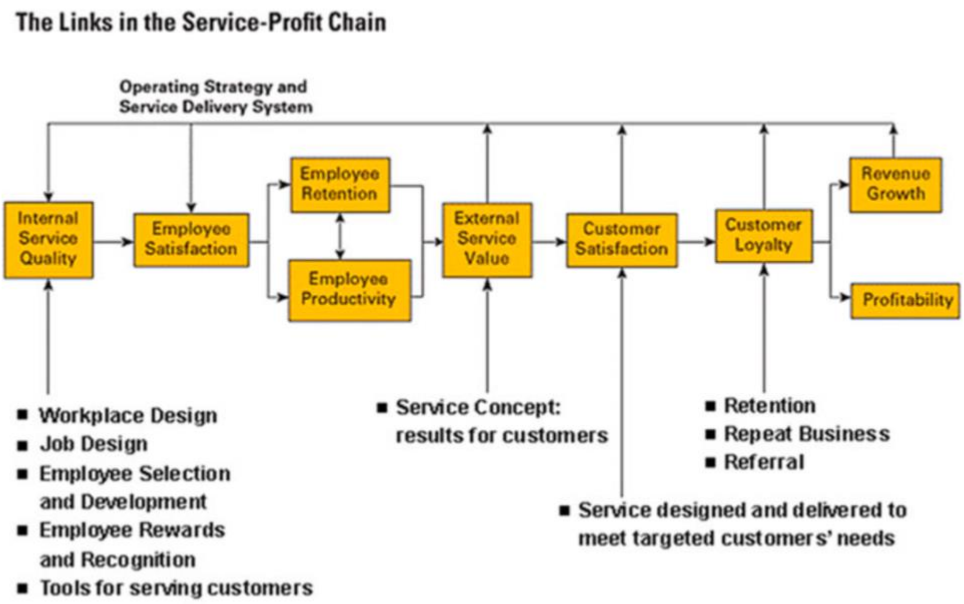

Figure 20. Illustration on the relationship between employee engagement and profitability. (Source: Ghatak 2022)

Figure 21 presents the links in the service-profit chain and how employee engagement, profitability and customer loyalty are related to each other in the sense of value creation. It is based on the notion that engaged employees often offer higher quality services for customers which in turn leads into higher level of customer satisfaction and therefore also customer loyalty with increase in profitability as well. (Ghatak 2022, 129-130) According to Cuganesan (2006, 172), offering value to customers is a common strategic goal amongst Australian banks, a fact that seems to be true also with Finnish banks as discussed in the previous chapter of this thesis. In his study Cuganesan (2006) states that when multiple organizations have same strategic goals, the execution of that strategic goals becomes the distinguishing factor. Therefore, linking internal HR data concerning employee surveys, work engagement, performance and turnover with internal non-HR data concerning CRM and financial performance data can help company X in increasing their performance in reaching that specific strategic goal. This same framework could also be used as a base with some alternations in solving another organizational challenge of the case company, namely proving the benefits of training investments through both increase in euros and in variety of products sold. This challenge is discussed in more detail later in this chapter through an example case.

Identifying potential and significant use cases for combining external data, HR on non-HR data, can be more complex. External HR data from the annual reports published by Finance Finland can be used in benchmarking purposes in reviewing where company X stands with respect to age, education and sex distributions. This benchmarking is significant in the sense that one of company X’s strategical goals involves operating and growing within a productive and responsible manner. Also, the workforce diversity and equality points of view can be considered important factors, the development of which in company X can be compared with other operators in the Finnish financial industry through benchmarking. As an example, the employee age distribution in the Finnish financial industry is presented in Figure 21.

Figure 21. Age distribution of the financial industry workforce in 2022. Legend: black bars = banks, grey bars = insurance companies (Source: Finance Finland, based on the wage statistics of Confederation of Finnish Industries)

External HR data can also be utilized in developing analytics solutions to aid in recruitment practices. In addition to using external HR data in traditional ways from platforms such as LinkedIn, analytics can help in automating certain steps of these processes. Already in 2000, Murphy and Zandvakili conducted a piloting experiment on computer-based employee selection at Kroger, a well-known grocery retail company in the USA. This experiment was based on relationships between a set of customer-related issues and employee characteristics determined earlier by the researchers. The goal of the experiment was to automate the first step of the recruitment process and provide store management with recommendation whether to hire the candidate or not. In addition to establishing the relationships between the variables, the desirable employee characteristics were studied prior the experiment. (Murphy & Zandvakili 2000, 101-102)

Company X could exploit similar framework to automate the first steps of its recruitment process. According to Murphy & Zandvakili, this would require identifying the relevant characteristics and skills for each role based on both the domain knowledge of each role as well as customer feedback. If customers' perspective is not available yet, it should naturally be studied. Whereas the experiment designed by Murphy & Zandvakili was carried out as a structured survey which was based on pre-determined relationships, with current analytical tools it would be possible to develop for example an algorithm that would compare the applicant's characteristics towards the desired characteristics of each role and help in pre-selection of the most suitable candidates for more detailed interviews. The implications of automating parts of recruitment practices were also a subject to study in the experiment of Murphy and Zandvakili, but as it was ongoing at the time of publishing the paper, the results were not determined yet. However, it was hypothesized that automating these practices would improve the selection and therefore have implications on financial performance of the organization. (Murphy & Zandvakili 2000, 102) This seems logical since automating practices should help in reducing costs through freeing resources and speeding up the processes.

6.5 Data quality and privacy

The importance of data quality is emphasized by multiple authors (Dahlbom et al 2016, Ghatak 2022, Marler & Boudreau 2017, Pillai & Sivathanu 2022, Wang et al 2024). In the study by Pillai & Sivathanu (2022, 3023), one of the main findings is the impact HR data quality has on the relationship between HR practice outcomes and HR metrics. This idea is also summarised in the study by Wang et al (2024, 1159), stating that the better the data quality, the more reliable the insights obtained and thus also the decisions made based on them. The concept of data quality covers several dimensions, the five most cited being completeness, accuracy, timeliness, consistency and relevance according to Wang et al (2024, 1170).

Since HR data quality was not brought up in the initial discussions concerning the development project, it was fair to assume that the case company had not experienced major challenges with it. This same conclusion could be derived from the interviews to some extent. The lack of significant problems with data quality can result from the descriptive level of analytics currently in use, manual reporting practice and the high level of domain knowledge amongst the HR employees. All these factors can contribute to the fact that major challenges with quality have possibly been identified and fixed manually ad hoc. Additionally, according to Wang et al (2024, 1173), large amount of data generally improves the decision-making quality. However, one interview revealed that there have been single cases where the beginning or ending day of an absence period has been failed to be updated, thus distorting the number of active employees within the temporal scope in question. Another interviewee discussed also how the data quality is not as high as it should be concerning the size of the case company. Considering the case of company X, it could be quite convincingly argued that all the errors with data quality are probably not identified since there is no person responsible for systematically monitoring data quality. On the contrary, employees making entries are jointly responsible for the quality of the data. Furthermore, data preprocessing can be considered a "best-practices" process. Therefore, it would be highly recommended for the case company to either hire a person responsible for data quality monitoring and management or appoint some of the current employees for the task. This solution would also help in managing and organizing the data in a way that would allow it to be more easily accessible and combinable for analytics purposes (Ghatak 2022, 91).

As company X operates in the Finnish financial industry, it is subject to many legislations and instructions (Finanssiala ry, finanssiala.fi) already on behalf of operators outside the company. These regulations include strict data privacy instructions, covering HR data as well. In practice, the data management privacy is monitored regularly by an information security team inside the company. Therefore, data privacy issues were decided to convincingly meet the standards required by the aforementioned legislations and regulations, thus being more than at satisfactory level considering the scope of this study.

However, as a result of one interview, it was noted that the practices designed to enhance data privacy cause challenges with data accessibility, combinability and reliability, therefore having direct impact on the development of HR analytics as well. The challenges discovered are caused by the data privacy structure dictating the data each employee has access to. In practice, this affects employees involved with HR reporting and analytics and their ability to access relevant data and combine it from different internal sources. Since combining HR data with data from various other sources is determined as one key characterization of HR analytics, a solution ensuring the accessibility to the relevant data across different organizational departments should be found.

6.6 HR metrics

Currently, company X reports HR metrics concerning demographical factors, working time and work arrangements, recruitment processes, occupational well-being, and skills and competence. Considering the number of metrics reported, company X reports 13 metrics monthly and 4 annually without including the entities comprising of demographical factors and employment contract key factors. This falls in the middle range compared to the participating four Australian banks in the study conducted by Cuganesan (2006), where the number of metrics reported were 6, 14, 15 and 22 in total per bank. As discussed in the theoretical part of this thesis, HR metrics can be classified into *financial or non-financial, quantitative or qualitative and lagging/descriptive or leading/predictive*. Using these classifications, the HR metrics currently reported by company X can be classified as presented in Table 5.

Table 5. Classification of company X's HR metrics.

Metric name	Financial	Non-financial	Quantitative	Qualitative	Lagging / descriptive	Leading / predictive
Full- and part-time contracts (no)		x	x		x	x
FTE (no)		x	x		x	x
Workforce mobility (no)		x	x		x	x
Turnover (by categories)		x	x		x	x
Overtime (h)		x	x		x	x
Open positions (no)		x	x		x	
Sickness absences (no)		x	x		x	
Sickness absence %		x	x		x	
Diagnostic categories		x	x		x	x
Health %		x	x		x	
Working time (h)		x	x		x	
Work engagement (score)		x	x		x	x
Demographic factors		x	x		x	x
Employment contract key factors		x	x		x	
Career development (no)		x	x		x	x
Competence development (€)	x		x		x	
Competence development (h)		x	x		x	
Employees having completed training (no)		x	x		x	x

Almost all the metrics reported are *non-financial* in nature, meaning that they describe the variable in some other terms than financial, for example in time or employees. In other words, there is only one metric, euros invested in competence development, that is expressed purely in monetary terms, i.e., as a cost of a certain practice. (Melnyk et al 2004, 212; Pillai & Sivathanu 2022, 3011-3012) If the case company would like to add the share of financial metrics, it would be possible to either transform some of the current metrics or develop new metrics based on them that could be classified as financial ones. For example, cost per hire is a financial metric calculated using the formula of overall hiring costs divided by the number of hires.

Concerning the division between *quantitative and qualitative metrics*, all the metrics are quantitative, meaning that the metrics use measurable data (Bortoluzzi et al 2018, 286). However, there can be cases when a metric primarily utilizing qualitative data can be expressed in its final outcome as a quantitative metric (Bortoluzzi et al 2018, 289). This is the case with work engagement metric, which comprises of multiple questions synthesizing the information into a single numerical output known as the work engagement score.

The third and final classification aspect deals with the temporal scope of information expressed by the metric or the impact the HRM practice measured has on the organization (Gabcanova 2012, 125). Classifying metrics in this sense is sometimes problematic since it can depend on how the metric is viewed, i.e., the same metric can be used both as a tool of evaluating development of a certain aspect and as a guiding metric for future HRM practices (Gabcanova 2012, 125; Pillai & Sivathanu 2022, 3012). While all the metrics of company X can be classified as *lagging or descriptive*, there are some cases when the information obtained can be used in the *leading or predictive* sense as well. Number of full- and part-time contracts, as well as FTE, are examples of such cases since they are presented for the executive team with budgeted figures. Thus, they are used in the planning of future recruitments in addition to expressing the number of employees with respect to each business function. Workforce mobility, turnover, overtime, diagnostic categories, work engagement, career development and number of employees having completed a certain training can be used in a similar manner as descriptive metrics but also in the planning of future HRM practices and evaluating the effectiveness and impact of these practices.

In addition to the aforementioned classifications, HR metrics include different levels depending on their focus (Dulebohn & Johnson 2013, 73; Pillai & Sivathanu 2022, 3011). Table 6 presents HR metrics of company X classified into *efficiency, effectiveness and impact levels.* Like the division between descriptive and predictive metrics, the classification between HR metrics levels is not always straightforward. Sometimes the same metric can be classified into more than one level depending on how it is viewed and interpreted, and which data sources it utilizes.

Table 6. Classification of company X's HR metric levels.

Metric name	Efficiency	Effectiveness	Impact
Full- and part-time contracts (no)	x		
FTE (no)	x		
Workforce mobility		x	
Turnover (by categories)		x	
Overtime (h)	x		
Open positions (no)	x		
Sickness absences (no)		x	
Sickness absence %		x	
Diagnostic categories		x	
Health %		x	
Working time (h)	x		
Work engagement (score)		x	
Demographic factors	x		
Employment contract key factors	x		
Career development (no)		x	
Competence development (€)	x		
Competence development (h)	x		
Employees having completed training (no)		x	

The number of full- and part-time contracts, FTE, overtime hours, number of open positions, working time hours, demographic factors, employment contract key factors and both competence development in euros and in hours are examples of HR *efficiency metrics* since they express the performance of HR within basic practices (Dulebohn & Johnson 2013, 73). The first two metrics, the number of full- and part-time contracts and FTE, express the size of the workforce in company X. Since these metrics are compared with budgeted figures for each business function, they express how efficiently the budget is being followed. Open positions can be used in evaluating how many positions there are open in each business function, i.e., how efficient the recruitment practices are. Working time and overtime provide information on how efficiently the working hours are distributed amongst the business functions and if there is extensive load in some areas. Metrics related to demographic factors such as age and gender distributions evaluate the structure and equality of the workforce, whereas employment contract key factors like the duration of contract and turnover percentage address HRM practice efficiency on this aspect. Competence development both in euros and in hours is similarly used to evaluate the efficiency of resource allocation and the cost of investment in competence development.

The remaining metrics can be classified into *effectiveness metrics* used in measuring the effect of the respective HRM practices (Dulebohn & Johnson 2013, 73). Workforce mobility measuring the number of new and terminated contracts expresses the effectiveness of HRM practices. Turnover and work engagement can both be used in evaluating the effectiveness of job satisfaction and practices related to it. While work engagement conveys information about the work experience as an entity, data obtained through turnover and exit interviews helps in understanding the reasons why turnover occurs. The metrics concerning occupational well-being, sickness absences (both the number of occurrences and %), diagnostic categories and health %, express how well the occupational health care practices are working and which are the most common diagnosis behind sickness absences. Through obtaining this information, the occupational health care practices can be improved further. Similarly, career development as the number of position transitions inside the company evaluates how effective company X is in offering career development opportunities for its employees and in practices enhancing it. The metric representing the number of employees having completed certain training is used to evaluate the effectiveness of training initiatives and their ability to reach employees.

The metrics belonging to the highest level of HR metrics, the *impact metrics*, express the impact of HR practices on organizational performance. Therefore, metrics representing this level are sometimes also called strategic metrics (Dulebohn & Johnson 2013, 74). While all the metrics described before are classified into efficiency and effectiveness metrics, they naturally affect organizational performance as well. For example, overtime can affect the occupational well-being of employees and therefore also productivity. However, as these metrics do not directly measure the impact of the certain HR aspect on organizational performance and do not involve combining data from other internal sources (Dulebohn & Johnsons 2013, 74), they are not classified as impact metrics in this study.

6.7 Organizational strategy implications on analytics

This chapter discusses how organizational strategy, and the strategic goals are reflected in the HR reporting currently conducted in company X. In the first subchapter, this aspect is studied from metrics' point of view followed by an example case discussing how company X could utilize HR analytics in solving an actual organizational challenge of the case company.

6.7.1 HR metrics

In their study Melnyk et al (2004, 209), state *"Metrics and strategy are tightly and inevitably linked to each other. Strategy without metrics is useless; metrics without a strategy are meaningless."* In other words, metrics measure the organization's performance in practices linked to the organizational goals (Cuganesan 2006, 165; Gabcanova 2012, 127; Salvadorinho et al 2022, 490) and should therefore reflect it well. As discussed in the theoretical part of this thesis, the development process of metrics should be carefully considered and involves understanding the affect HRM practices have on organizational performance and strategy (Cuganesan 2006, 168; Gabcanova 2012, 127; Schwarz & Murphy 2008, 170). In Figure 22, the HR metrics reported by company X are presented with respect to the strategic goals of the company.

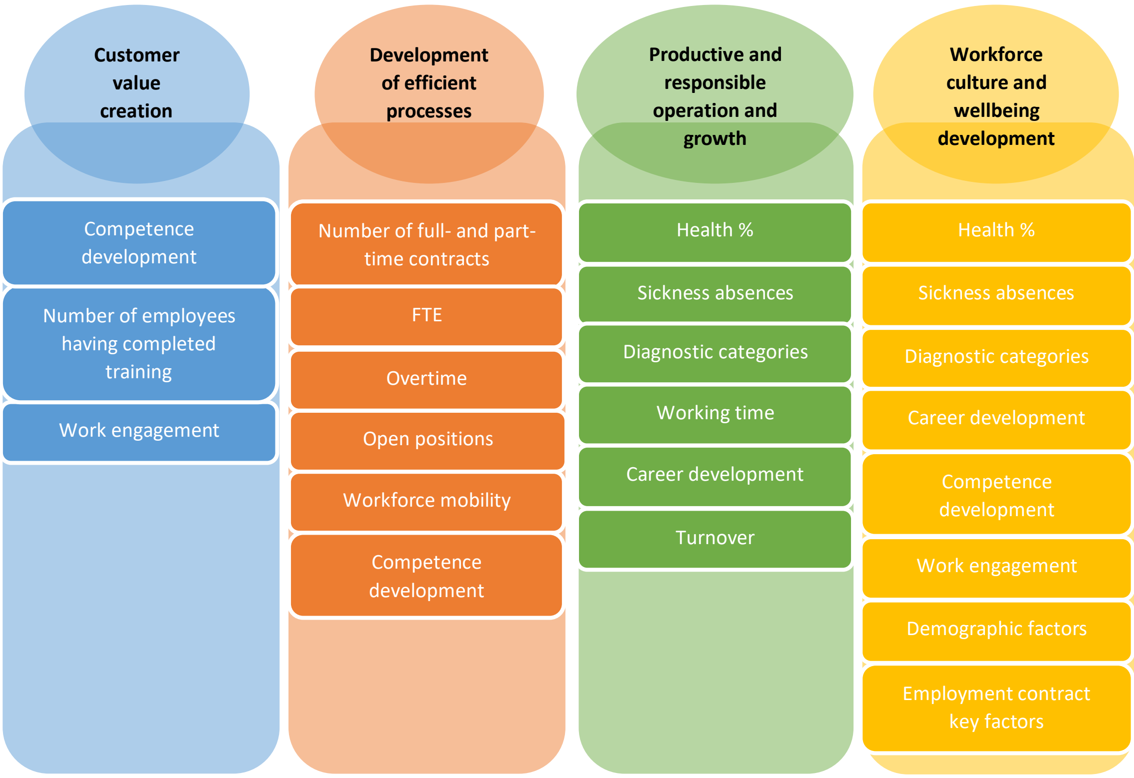

Figure 22. Company X's HR metrics with respect to strategic goals.

The currently reported HR metrics represent all the strategic goals of company X. By just examining the distribution of the metrics across the different goals, it can be said that each goal has representative metrics assigned, some metrics even represent multiple goals. However, some goals are not represented comprehensively since the reporting of some metrics is conducted only on annual basis, i.e. the reporting of these aspects is not sufficient in the timely sense.

The first strategic goal, *customer value creation*, is represented from competence development and employee engagement points of view. Since employee competence and engagement affect the quality of the customer service and therefore also customer satisfaction, as illustrated earlier in this chapter in Figure 21, the use of these metrics as representatives of this strategic goals is justifiable. However, since metrics dealing with skills and competence are reported only on annual basis, work engagement is the only representative of this strategic goal reported regularly. Therefore, increasing the reporting frequency with these metrics as well as combining the data from other sources such as customer satisfaction, would improve the level to which the success of reaching this goal is measured.

The second strategic goal, *development of efficient processes*, includes the aspects of competence development, recruiting and the size as well as the utilization level of the workforce. As discussed with the metric levels, the number of full- and part-time contracts and FTE express the size of the workforce, and together with the budgeted figures, how successfully these budget plans are met. Overtime is used to evaluate how efficiently the workforce meets the demand in each business function in addition to how efficient the processes inside the functions are in the first place. Workforce mobility, and especially high level of terminated contracts, might indicate inefficient HRM processes with employee turnover. Similarly, the number of open positions is used in evaluating the efficiency of the recruitment processes. The final metric in this group, competence development, represents the investments used in training employees and thus enhancing process efficiency.

The metrics associated with the third strategic goal, *productive and responsible operation and growth*, have implications on productivity or responsible way of operating. If company's turnover is high, it inevitably affects the productivity of the company. This is also the case with occupational wellbeing, since high sick absence percentage or low health percentage have both implications on productivity. In addition, monitoring the working time and different diagnostic categories contributes to responsible operation through ensuring at the same time reasonable and productive working hours while identifying also problem points concerning occupational wellbeing which should be addressed.

The final strategic goal, *workforce culture and wellbeing development*, has the most metrics associated with it. This goal is represented from the occupational wellbeing and engagement, career and competence development aspects including also metrics addressing demographic factors and employee contract key factors. However, as noted earlier, metrics concerning skills and competence as well as career development are not reported regularly, which affects the reflection of success in these aspects.

6.8 Example case: Proving the benefits of training investments

As stated by multiple authors (Angrave et al. 2016, 9; Huselid 2018, 683; Mattson 2018, 24; Rasmussen & Ulrich 2015, 238; Saramies & Törnroos 2021, 98; van Vulpen, Academy to Innovative HR 2024), HR analytics project should always start with an organizational challenge. The chosen challenge should be such, that solving it offers significant value for the organization or otherwise solves a problem that has been identified as a critical one by several different parties (Fitz-enz 2009, 3; Rasmussen & Ulrich 2015, 238; Saramies & Törnroos 2021, 99-102). In addition, Saramies & Törnroos (2021, 99) encourage organizations to start implementing HR analytics with a single project and develop the skills further through experience gained and feedback received.

In the initial meetings concerning this thesis, company X stated proving the benefits of training investments as one of the challenges to be solved using HR analytics. The selection on this challenge is justifiable since it has implications on the strategic goals and addresses the gap in reporting the skills and competence aspect. Proving the benefits of training investments is likely to increase since training deductions for companies are removed in 2025 (Veronmaksajat, 2024). The challenge of proving the benefits was already briefly touched upon earlier in this chapter dealing with the use of data sources in HR analytics projects. For the benefit of the case company, this challenge is discussed in more detail in this subchapter. However, it should be noted that since the empirical part of this thesis was agreed to be executed as a qualitative study, the following discussion does not include conducting actual data analysis or analytics and is based purely on theoretical knowledge. Therefore, it is not possible to evaluate whether this suggestion is possible to be implemented with the data that is actually available and can be used purely as a general framework.

According to the HR analytics project steps based on Mattson (2018) and van Vulpen (2024), the second step of the process comprises of identifying the appropriate data sources used to solve the challenge. In addition to affecting the data sources to be used (Coron 2022, 1398), the organizational challenge also guides the selection of the analytics method (Saramies & Törnroos 2021, 179-180). Table 7 presents possible metrics of company X to be used as variables in solving the aforementioned organizational challenge as well as their data sources and types.

Table 7. Suggestions as variables for proving the benefits of training investments in company X.

Variable	Data source	Data type
Competence development (€)	Internal HR-data	Skills and competence
Competence development (h)	Internal HR-data	Skills and competence
Employees having completed training (no)	Internal HR-data	Skills and competence
Overtime (h)	Internal HR-data	Working time
Turnover (no by categories)	Internal HR-data	Job satisfaction
Work engagement (score)	Internal HR-data	Job satisfaction
Errors detected (no)	Internal HR-data / non-HR data	Skills and competence / internal audition
Customer complaints (no)	Internal non-HR data	CRM
Customer satisfaction score	Internal non-HR data	CRM
Service events (no)	Internal non-HR data	CRM
Product sales (€)	Internal non-HR data	Finance
Product sales (items)	Internal non-HR data	Finance

Since company X already has these metrics in use, one possible solution for proving the benefits of the training investments would be simply to follow the development in these metrics, i.e. determining the values before and after the training has taken place. However, it should be considered how the other factors possibly contributing to the changes are controlled. This could be addressed for example by dividing the employees into two groups, one group participating in the training which effects are studied and the other not. Also, to determine if the changes occurred in the metrics are statistically significant, appropriate statistical methods, for example the t-test, should be used. T-tests achieve this goal by comparing the means of two groups and they can be run for example in R and Python, both mentioned previously in this chapter. Nevertheless, it should be also noted that that there is a difference between a statistically significant and a practically significant result.

Another solution for the challenge involving the use of higher-level analytics could be the use of correlation or regression analysis. Again, also these analysis can be performed either with R or Python. Regression aims to express and model the relationship between a target variable and one or more variables of interest, the changes in which are hypothesized to cause changes in the target variable as well (Brooks 2008, 27). The target variable is usually called the dependent variable and the other variable(s) the independent variable(s). With this specific organizational challenge, a regression analysis could be carried out by first choosing the dependent variable that is to be used as the metric to express the benefit gained from the training investments. For example, if the increase in value created through training is to be examined from the financial aspect, product sales in euros would be a suitable target variable to be used as the dependent variable. After the dependent variable is chosen, the variable(s) which effect on the dependent variable are to be examined are chosen. If there are more than one independent variable, the method is called multivariate regression. Through estimating the regression model, the hypothesis stating that training investments lead to increases in product sales can be tested. It should be noted, however, that the relationship between the dependent and the independent variable(s) can be various in its nature. While a linear regression model is probably the most known, the relationship between the variables can exist in other forms as well, for example as an exponential relationship. However, these relationships can usually be transformed into linear relationships if necessary. (Brooks 2008, 38-39)

Correlation addresses the relationship between variables in the sense of direction and strength of the relationship. In other words, if two variables are stated to be correlated, it is assumed that there exists a linear relationship between them. (Brooks 2008, 28) If two variables are negatively correlated, i.e. increase in one variable cause decrease in the other, the sign of the correlation coefficient is negative. Correlation coefficients are presented as values between -1 and 1. The correlation coefficient -1 represents a perfect negative correlation, 0 no correlation between variables and 1 perfect positive correlation. Correlation analysis is fast and simple to carry out using either R or Python by running a code dedicated for the function. However, as noted earlier in this chapter, correlation does not necessary imply causation (Brooks 2008, 28), therefore the results obtained should be considered with care and justified also with either theory or expert opinions.

Compared with each other, correlation assumes linearity between the variables while regression allows modelling of other forms of relationships as well (Brooks 2008, 28, 38-39). Regression can also be used to predict the future values of the dependent variable based on the values of the independent variable(s) whereas correlation analysis can be used to examine if certain variables correlate with each other. In other words, correlation analysis is descriptive in its nature while regression can be used on the predictive level as well. According to the interview with one of the development managers, company X has already carried out some experimental analysis to identify relationships between work engagement and occupational wellbeing. These experiences and routine gained through them could be exploited with this project as well.

Before using any analytics method, however, data preprocessing should be conducted to ensure high data quality to be used in the decision-making. As discussed earlier in this chapter, data quality affects the quality of the insights obtained from data and therefore also the quality of the decisions made (Wang et al 2024, 1159). Data preprocessing begins the third step of the HR analytics process and includes practices aiming to enhance data quality on different dimensions. According to Wang et al (2024, 1170) the five most cited data quality dimensions in literature are completeness, accuracy, timeliness, consistency and relevance. Performing exploratory data analysis also aids in understanding the data better and therefore the suitable processes and methods to be executed with it.

In the last two steps of an HR analytics project, actionable insights are made from the analytics results. With this example case, these insights would address the relationship between training investments and profitability gained from them, as well as other possible factors affecting the profitability. In the simplest case where changes occurring in the metrics are monitored, these insights can be determined from the differences in the results obtained between the test and control groups and in the case of correlation analysis from the correlation coefficients. With regression analysis the insights are also formed from the coefficients, but as stated before, regression analysis can be additionally used to make predictions about future. The final step comprises of follow up analysis, i.e., recreating the study on regular basis to discover changes occurring or possible trends present.

In addition to the organizational challenge discussed above, the case company could utilize same methods for similar challenges. For example, regression analysis could be used in determining the most important skills with respect to the performance metric of choice and correlation analysis in determining the possible correlations between certain skills and performance metrics. Predictive analytics could also be used in discovering which skills would be necessary in different future scenarios, e.g. what are the implications of turnover and workforce health on critical skills. All these analyses could prove useful in securing the desired level of critical skills needed for completing the most important practices inside the company. This challenge also has implications on several organizational goals, and therefore presents an interesting topic for further study.

6.9 Summary

This chapter has combined the knowledge obtained through the theoretical part of the thesis with the results of the empirical study. By combining this information, the current state of the case company with respect to HR analytics has been evaluated using the key concepts identified in the theoretical part with a focus on concepts directly related to reporting and analytics. Furthermore, suggestions for developing the HR analytics within the case company have been given. The key challenges identified through this process with measures suggested for addressing them are summarised in Table 8 below.

Table 8. Key challenges of company X and measures suggested for addressing them.

Challenge / Development target	Measure(s) suggested
Talent gap in data and analytics expertise	1) Specialization training of current employees with respect to analytics, statistical skills and data quality monitoring 2) Hiring or consulting data analyst and data quality manager
Communicating the level of success in reaching each organizational goal	Establishing scale & base values for reaching each goal followed by regular measurement & visualization of the success achieved
Lack of regular measurement of the skills and compentence dimension	Increasing the reporting interval of this dimension
Routine reporting conducted manually	Automating routine reporting
Reporting on descriptive analytics level using HR metrics	Implementation of more sophisticated analytics methods, for example correlation & regression analysis and more versatile utilization of analytics maturity levels
Microsoft Excel as primary analytics tool	Implementation of more sophisticated analytics tools, for example R or Python
Utilization of solely internal HR-data	More versatile use and combining of internal HR- and non-HR data as well as external HR- and non-HR data
Proving the benefits of training investments	1) Monitoring development in relevant HR metrics, controlling other contributing factors by using control groups, testing the significance of the results using T-tests 2) Use of correlation and/or regression analysis

The talent gap identified in data and analytics expertise is suggested to be solved through either offering specialization for current employees or investing in consulting services. This includes both analytical and statistical skills needed with more complex analytics methods and data quality competence for regular monitoring of HR data quality. Alternatively, hiring or consulting data analyst and data quality manager to bridge these gaps is proposed. However, it should be taken into consideration that consulting only addresses short-term needs and is therefore probably not a sustainable option.

Considering the challenges related with analytics levels, methods, tools, processes and data sources, the currently used routine reporting of HR metrics is suggested to be automated. Also, the reporting interval of skills and competence dimension is recommended to be increased in order to reflect the organizational goals more comprehensively. Additionally, the clarity in communicating the success of reaching each organizational goal is proposed to be increased by establishing scale and visualizing the results. More sophisticated analytics methods from higher analytics maturity levels are introduced through an example case. Furthermore, the use of free programming languages R and Python are discussed as well as a more versatile utilization of data sources from in- and outside the company.

7 Conclusions and Discussion

The aim of this thesis has been to contribute to the research gap identified with the use of HR analytics in the financial industry. Since it was noticed that the literature within this scope is scarce, the literature review part was decided to be expanded to include also literature addressing knowledge-intensive organizations and other quantification methods used in HRM. The research was conducted in co-operation with a case company operating in the Finnish financial industry.

Through carrying out a qualitative case study, this thesis determined the current situation and level of HR analytics in the case company. Additionally, the study also provided case company with some improvement suggestions for developing their HR analytics further. Compared to the research previously carried out considering the topic in the financial industry, this study adopted a more comprehensive perspective, examining multiple aspects simultaneously within a single company. The results of the study show that the current level of HR analytics within the case company is at the descriptive level. The methods utilized consist mainly of various HR metrics reported manually with Excel either monthly or annually. The employee competence with respect to analytical and reporting skills reflects the level of analytics in use. The use of data sources is currently monotone and includes internal HR data only. Additionally, there is no regular controlling of HR data quality, and the data privacy structures pose challenges for combining data from different business functions.

7.1 Implications

The research implications of this thesis can be divided into theoretical and practical ones. The main theoretical implication is the contribution to the research considering HR analytics, especially seeking to bridge the gap in studying the use of it in the financial industry. Considering practical implications, this thesis has performed an evaluation of the current situation of HR analytics in the case company. As this evaluation is based on key concepts derived from the literature, it offers the case company a comprehensive overview on justified concepts identified significant by multiple scholars. In addition to the evaluative overview provided, this thesis has made improvement suggestions for developing the HR analytics further inside the case company. These suggestions include the most significant concepts identified through theory with a focus on concepts directly related to reporting and analytics practices. The managerial implications of this thesis focus on improving the analytical and statistical skills and competence amongst employees as well as increasing data quality management and adopting of more sophisticated analytics tools.

RQ1: What kind of HR analytics or HR metrics solutions and other HRM quantification approaches exist in the financial industry or in the knowledge-intensive organizations? What are the key concepts of these?

The research discovered during this thesis process indicates the strong use of regression analysis as a method of conducting HR analytics in the financial industry. In two out of three research works identified, regression models are used to identify the determinants of absenteeism and the branch level performance of a financial institution. The remaining research work focuses on analysing the level and focus of the KPIs reported by the case companies. While there is an extensively larger amount of research carried out in the knowledge-intensive organizations on the topic, the HR analytics solutions introduced in the research works mainly discuss the use of HR metrics and KPIs. This coincides with the notion that research on HR analytics discusses the topic on a general level without specializing in individual industries. Also, there exists a substantially greater quantity of research on HR metrics and KPIs than on HR analytics. This is natural, since metrics is an older and therefore also more researched topic, as discussed in the subchapter presenting HR analytics evolution. Other quantification approaches used in HRM that were identified through the literature review are HR scorecard and HR accounting.

The key concepts identified from the literature included in the review are: employee competence with relation to analytical and reporting skills, employee performance measurement, evidence-based management culture and the communication of the results, HR data quality, privacy and utilization of data sources, analytics maturity levels, methods and tools as well as HR metrics classification, levels and the implications of the organizational strategy on analytics.

RQ2: What is the current state of HR analytics in company X and how could it be developed further?

The current HR analytics executed in company X consists almost entirely of analytics from the descriptive level and comprises of various HR metrics reported either monthly or annually with Excel. The employee competence with relation to skills necessary in conducting HR analytics reflects the current level of analytics utilized within HR reporting, i.e., there is a talent gap in skills associated with more complex analytics and statistics. Data related concepts were evaluated from the data quality, privacy and data source utilization aspects. Considering data quality, it was found that there is no regular HR data quality monitoring at use. Data privacy was discussed from data accessibility and combinability point of view, and it was noted that the data privacy structure of company X results into challenges with accessing and combining data from other departments of the company. What comes to data source utilization, company X currently utilizes solely internal HR-data, i.e. internal non-HR data and neither external HR data nor non-HR data are utilized.

The main development recommendations address the need to improve the analytical and statistical skills amongst employees as well as developing a regular data quality management solution that is currently missing. These factors are considered to set the biggest challenges necessary to be solved to move to the more sophisticated analytics methods and solutions. As a solution, this thesis suggests either providing the existing employees with training to acquire the necessary skills or creating entire new positions for these roles. Since combining HR data with data from other departments is one of the key characterizations of HR analytics, solving also the challenges resulting from the strict data privacy regulations are crucial. Solving the data privacy challenge is more complex since the data accessibility is automatically dictated by the system and depends on usage rights granted for each employee according to their role. Thus, solving this challenge requires decisions directly from higher level. After the data combinability challenge is solved, a more versatile use of internal non-HR data as well as external HR- and non-HR data is recommended with some example cases.

As a part of development suggestions, this thesis briefly presents alternative analytics tools for conducting HR analytics, namely free programming languages R and Python. The example case discussed presents a compact description of the use of correlation and regression analysis with the specific organizational challenge in question. Furthermore, the reporting interval with the skills and competence dimension is suggested to be made more frequent to measure the success in reaching the relevant strategic goal. Also, developing a visual method for demonstrating the success in reaching each strategic goal would increase the understanding amongst employees of the current situation.

7.2 Verification and Validation

7.2.1 Limitations

The main limitations considering this study are related to geographical, temporal, and methodological aspects. This thesis has examined the research topic in a single Finnish case company with a limited temporal scope. Thus, this naturally affects the repeatability and generalizability of the study, and the insights obtained. In practice, this means that the findings of this study may not be repeatable or generalizable within other countries or companies since they represent solely the current situation of a single company with limited temporal scope. The single case study setup also affects the ability to make comparative notions about concepts, which also contributes to generalizability of the results.

Additionally, as this study was carried out as qualitative study, there are some limitations resulting from the methodological choice made. The main limitations concerning this aspect are related with interpretation of the results as well as the fact that the research did not include actual work with data. Unlike most quantitative data, qualitative data can be interpreted in multiple ways. Therefore, even though this thesis has aimed for justifying the evaluations made based on theory, there might be some bias resulting from subjectivity, affecting the reliability of the study. Also, the improvement suggestions made are based on theory, which might prove unsuitable with actual data due to special characteristics of the data itself or the amount of data available.

7.2.2 Future research suggestions

The research conducted so far on HR analytics has been mainly theoretical in its nature, empirical research forming a considerably smaller part. Therefore, studying the subject empirically based on the theoretical knowledge already formed through various studies and testing the theories in practice would add depth into the research.

Considering future research suggestions further, this thesis has showed that there is a gap in the research on the use of HR analytics in the financial industry. While this thesis has contributed to bridging this gap, it has done it with respect to a single case company. Therefore, future research should focus on studying the use of HR analytics in the financial industry more comprehensively. The existing research has been conducted with small samples and has been published in the early 2000's. As the development around the topic has been rapid, it would be worth of conducting an update on a larger sample, addressing the overall situation on the industry which remains not yet studied.

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Appendix 1. Search queries and results: EBSCO.

			EBSCO		
Search query no	**Search group**	**Search words**	**Results**	**Relevant**	**Irrelevant**
1	1	hr analytics or people analytics or human capital analytics or workforce analytics or talent analytics or human resource analytics or employee analytics	2	0	2
	2	metrics or kpi or key performance indicator or kpis or key performance indicators			
	3	banking industry or banking sector or banks or financial institution or financial sector or financial industry or capital markets			
2	1	hr analytics or people analytics or human capital analytics or workforce analytics or talent analytics or human resource analytics or employee analytics	31	5	26
	2	metrics or kpi or key performance indicator or kpis or key performance indicators			
3	1	human resources or hr	65	4	61
	2	metrics or kpi or key performance indicator or kpis or key performance indicators			
	3	banking industry or banking sector or banks or financial institution or financial sector or financial industry or capital markets			
4	1	human resources or hr	24	3	21
	2	metrics or kpi or key performance indicator or kpis or key performance indicators			
	3	knowledge management or knowledge sharing or knowledge transfer or evidence based management			
5	1	human resources or hr	5	*2	3
	2	metrics or kpi or key performance indicator or kpis or key performance indicators			
	3	employee expertise or knowledge worker or knowledge based services			
6	1	human resources or hr	1448	-	-
	2	metrics or kpi or key performance indicator or kpis or key performance indicators			
7	1	human resources or hr (in title)	18	9 (*4)	9
	2	metrics or kpi or key performance indicator or kpis or key performance indicators (in title)			
			* found already in earlier search		

Appendix 2. Search queries and results: ScienceDirect.

		All in title, abstract or author-specified keywords	ScienceDirect		
Search query no	**Search group**	**Search words**	**Results**	**Relevant**	**Irrelevant**
1	1	hr analytics or people analytics	0	0	0
	2	metrics or kpi or key performance indicator			
	3	banking or financial or capital markets			
2	1	hr analytics or people analytics	1	*1	0
	2	metrics or kpi or key performance indicator			
3	1	human resources or hr	18	0	18
	2	metrics or kpi or key performance indicator			
	3	banking or financial or capital markets			
4	1	human resources or hr	4	0	4
	2	metrics or kpi or key performance indicator			
	3	knowledge management or knowledge sharing or knowledge transfer or evidence based management			
5	1	human resources or hr	1	0	1
	2	metrics or kpi or key performance indicator			
	3	employee expertise or knowledge worker or knowledge based services			
6	1	human resources or hr	492	-	-
	2	metrics or kpi or key performance indicator			
7	1	human resources or hr (computer & social science, business, management & accounting)	22	3(*2)	19
	2	metrics or kpi or key performance indicator			
			* found already in earlier search		

Appendix 3. Search queries and results: LUT Primo.

			Primo		
Search query no	**Search group**	**Search words**	**Results**	**Relevant**	**Irrelevant**
1	1	hr analytics or people analytics or human capital analytics or workforce analytics or talent analytics or human resource analytics or employee analytics	1	0	1
	2	metrics or kpi or key performance indicator or kpis or key performance indicators			
	3	banking industry or banking sector or banks or financial institution or financial sector or financial industry or capital markets			
2	1	hr analytics or people analytics or human capital analytics or workforce analytics or talent analytics or human resource analytics or employee analytics	42	*4	38
	2	metrics or kpi or key performance indicator or kpis or key performance indicators			
3	1	human resources or hr	176	-	-
	2	metrics or kpi or key performance indicator or kpis or key performance indicators			
	3	banking industry or banking sector or banks or financial institution or financial sector or financial industry or finance or capital markets			
4	1	human resources or hr **(in subject)**	37	0	37
	2	metrics or kpi or key performance indicator or kpis or key performance indicators **(in subject)**			
	3	banking industry or banking sector or banks or financial institution or financial sector or financial industry or finance or capital markets **(in subject)**			
5	1	human resources or hr	72	-	-
	2	metrics or kpi or key performance indicator or kpis or key performance indicators			
	3	knowledge management or knowledge sharing or knowledge transfer or evidence based management			
6	1	human resources or hr **(in subject)**	26	*1	25
	2	metrics or kpi or key performance indicator or kpis or key performance indicators **(in subject)**			
	3	knowledge management or knowledge sharing or knowledge transfer or evidence based management **(in subject)**			
6	1	human resources or hr	12	2 (*1)	10
	2	metrics or kpi or key performance indicator or kpis or key performance indicators			
	3	employee expertise or knowledge worker or knowledge based services			
7	1	human resources or hr	2815	-	-
	2	metrics or kpi or key performance indicator or kpis or key performance indicators			
8	1	human resources or hr **(in title)**	45	7 (*3)	38
	2	metrics or kpi or key performance indicator or kpis or key performance indicators **(in title)**			
			* found already in earlier search		

Appendix 4. Interview questions.

Role, education and motivation

1. What is your role in company X?
2. How long have you worked in this role?
3. What is your educational background, and does it involve studies in analytics or reporting?
4. In what roles have you worked before? Have these roles included the use of analytics or reporting?
5. Do you participate in reporting? If so, how long have you been doing it?
6. Have you received internal training for the use of analytics or reporting?
7. How interested are you in developing your competence in analytics and reporting?

Reporting

1. What is the history of HR reporting in company X? How long has it been conducted in its current form?
2. What does HR reporting currently include? E.g. metrics.
3. How are these metrics chosen?
4. How would you describe the ease of reporting and the usability of the reporting results?
5. Which reporting systems do you use?
6. Which analytics tools do you use?
7. Who is/are the recipient(s) of the reporting?
8. What is the current reporting interval?
9. How would you like to develop the HR reporting?

Occupational wellbeing data and employee surveys

1. What kind of dimensions are included in the employee surveys? What about in occupational wellbeing data?

2. How is occupational wellbeing monitored? What metrics does it include?
3. Who monitors these metrics?

Data (management, quality, sources)

1. How do you see the quality of the data?
2. Who is responsible for data quality?
3. How is the data stored?
4. What data sources are used in HR reporting?

Utilization and communication of reporting results

1. Are the reporting goals communicated clearly enough?
2. How are the reporting goals and results communicated for the employees?
3. Are the reporting results used in management and decision-making? What are the use cases of the reporting results?
4. Do you feel that the management is committed in investing resources in HR practices and development of HR analytics? Is it easy to acquire resources for projects?
5. How strong is the evidence-based management culture in company X? Are there differences between business departments?

Organizational role, strategy and its implications in HR practices and reporting

1. Do you know what are the strategic goals of company X?
2. How are these goals reflected in the HR practices and reporting?
3. How would you describe the organizational role of HR? Is it more administrative or strategic?