The implications and impact of artificial intelligence, big data and HR analytics in HRM: A critical analysis of EU enterprises

KIU, CHUN,TUNG,THOMAS

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Author: Chun Tung Thomas Kiu

Supervisor: This thesis was discussed with Dr. Bechter and Prof. Brandl, Business School, Mill Hill Lane, Durham DH1 3LB

Abstract

This study offers a critical evaluation of HR analytics. Specifically, the ideas and concepts surrounding HR analytics, such as what is HR analytics, the development of HR analytics in organizations and how it may impact organizational performance. To advance and answer these research questions, this study relied on systematic reviews, logistic regression, interaction effect analysis, and interviews with the European Company Survey (ECS) to assess the interrelationship between HR analytics and organizational factors. Based on the findings, certain key areas are addressed. Firstly, research question 1 has succeeded in developing a more systematic and coherent definition of HR analytics and artificial intelligence in HR. It has also successfully identified some factors that influence the use of HR analytics in organisations. In particular, the results of study two found that factors such as firm age, firm size, the complexity of the firm process and the type of variable pay systems have been shown to be key indicators of why certain companies use HR analytics while others do not. Furthermore, the results for study three also provided a bigger picture of how organizational factors might be the reasons for explaining firms' financial returns when examining the relationship between variables. In particular, factors such as employee motivation, the use of HR analytics, and variable pay systems are also believed to be critical in determining which factors affect a company's financial returns. In addition, the study provides additional knowledge for five specific areas in analytics and artificial intelligence in HR, namely firm characteristics, challenges, key reasons to adopt HR software, new trends and user traits.

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List of Abbreviation

HPWS: High-Performance Work System

SHRM: Strategic Human Resource Management

Contents

Table of Contents

Chapter 1: General Introduction

1.0. Introduction

Human Resource Management (HRM), the management of people to achieve desired goals, is a fundamental activity in any organisation, and with the advent of new technology, many traditional HR tasks are now automated. The focus is on managing people, with an emphasis on strategy and policy. According to strategic HRM literature (Appelbaum et al., 2000; Tsui & Lai, 2009; Vipul, 2019), HR function should be aligned with business objectives and employees should be seen as a competitive resource for the company to succeed in a highly competitive market. Given the developments in applications of analytics and artificial intelligence, it is not surprising to see the surging rise in human resource (HR) related technology from which the industry has experienced tremendous growth in the past two decades. We have seen nothing like this that has changed the ability of information technology (IT) that impacts human activity so profoundly since the industrial revolution in the late 18th and early 19th centuries. The rapid development of hardware, together with the continuous innovation of software has not only changed the way people work but also how businesses manage their workforces (Barley, 2020). From recruitment automation to performance evaluation, new applications do have their parts in dealing with different aspects of HR activity.

Since the early 2000's corporations have moved from using traditional technology to handle standardized tasks such as screening resumes and payroll calculations to more strategic uses of information and data analytics. The rapid development and proliferation of software technology are having a significant impact on business operations and providing companies with new opportunities to transform data into useful information (Smith, 2020), which will facilitate effective and objective decision making grounded in data. By observing and analysing information carefully, managers can now effectively forecast the future and ultimately achieve their objectives to gain competitive advantages. Analytics is now used in various departments, such as marketing, finance and human resource management (HRM). However, for the purpose of this thesis, the focus will be on the perspective of HRM and how analytics may contribute to the HRM function. The realisation of the potential benefits of software technology, such as human resource analytics (HR analytics) is gaining some momentum among academics and practitioners (Eubanks, 2019; Huselid, 2018; Marler & Boudreau, 2017; Nilsson, 2018). This paper aims to highlight several important aspects of HR analytics and its relationship with artificial intelligence.

There are three aims of this thesis. The first part of the paper will provide an overview of the current literature on HR analytics and develop a more coherent definition. The second part of this thesis attempts to test a list of factors that influence the incidence of HR analytics as well as the interaction effect between HR analytics, variable pay systems and a company's performance. Specific questions are listed below.

1) **How to develop a more consistent definition of HR analytics and HR artificial intelligence.**
2) **What factors influence the use of HR analytics from a company perspective? Specifically, how does the complexity of HR systems and variable pay systems influence the use of HR analytics?**
3) **Does HR analytics have an impact on a company's performance?**

In addition, the structure of the thesis is as follows: It will first start with a general introduction to the whole topic. Then it will focus on study one, followed by study two and study three. And at the end, there will be a general conclusion to summary the findings and contributions. However, it is important to note that these three studies are closely related to each other.

1.1. Research contribution

First, the study extends the limited research on understanding HR analytics and its definition. Our study is one of the first to look at HR analytics and artificial intelligence in different lens and suggest that a clearer definition might enhance their development and reduce confusion when discuss such topics in both industry and research communities.

Second, evaluate the different firm characteristics between variables. This will help explain the mechanism by which characteristics can influence a firm in adopting HR analytics. This will provide the research community with a more complete picture of why some firms make use of the potential of HR analytics for monitoring the performance of employees while others do not.

Third, to the best of the author's knowledge and by searching peer-reviewed databases, no previous study has empirically examined the impact of HR analytics on firm financial performance and its interaction with employee motivation and the variable pay system. Therefore, by evaluating this relationship, we would be able to understand whether or not HR analytics can provide additional benefit beyond the individual main effects of the variables involved.

Fourth, the qualitative portion of the study also reinforces the idea that a company's financial performance can vary greatly depending on how a company deploys its HR analytics system. In other words, this part of the study highlights the key areas a company needs to pay attention to in order to maximize the chances to gain a competitive advantage (i.e., firm characteristics, challenges, key reasons to adopt HR software, new trends and user traits).

1.2. Background knowledge

Fundamentally, HR analytics is a tool that transforms data into HR topics and it is becoming a popular topic among academics and business professionals. Regarding the former, researchers have endeavoured to explore aspects of the relationships within its multifaceted nature. Recent studies include those that focus on the field of HR analytics in general (Ben-Gal, 2019; Marler & Boudreau, 2017; Mohammed & Quddus, 2019), to those which address the usefulness of HR analytics (Aral et al., 2012; Dahlbom et al., 2019; Eubanks, 2019; Hoffman et al., 2017; Levenson, 2011; Schiemann et al., 2018; Wang & Cotton, 2018), to those who concentrate on HR professionals' skill sets (Kryscynski et al., 2018) and to those who look into the challenges professionals might face when adopting HR analytics, such as data gathering, data cleansing and the knowledge and skills needed to implement and understand analytics results (Angrave et al., 2016; Dahlbom et al., 2019).

Regarding the latter, the management and strategy consulting companies have placed particular focus on the effectiveness of HR analytics and provided reasons why organizations should adopt such practices. For instance, numerous business reports published by Deloitte, KPMG, PwC and McKinsey focused predominantly on how HR analytics has the ability to assist organizations to achieve competitive advantage. For example, selecting high performers, reducing recruitment costs and better managing workforces (Bughin et al., 2017; Collins et al., 2017; KPMG 2013; Kukde, 2016; PwC, 2020). Based on a report published by Deloitte, researchers suggested that "HR analytics is a business discipline, supporting everything from operations and management to talent acquisition and financial performance" (Collins et al., 2017, p.7). While KPMG (2013, p.2) said that "HR analytics can provide a tangible link between your people strategy and your organization's performance". Given the above literature and reports, it is sensible to assume that the pursuit of knowledge regarding their interaction with and impact upon HR analytics has been and continues to be of vital importance to academia and the business industry.

The main idea of this chapter is to present an overview of HR analytics, as well as the methodological and theoretical parameters of the thesis. This not only concretizes the above research topics in the exploratory field of literature but also provides theoretical and methodological insights into how the process of this thesis has been developed. Subsequently, the key findings and contributions are presented as a whole in a well-structured framework. In addition, the literature on HR analytics (e.g., Big Data and artificial intelligence in HR) is also considered to provide a comprehensive overview to answer the three research questions listed above.

1.3. Context

Academics literature on HR analytics is still in the exploratory phase and may require more evidence to formulate more robust findings. Numerous researchers are contributing to this topic by conducting an evidence-based review using an integrative synthesis of the published peer-reviewed literature on HR analytics (Ben-Gal., 2019; Marler & Boudreau, 2017). Researchers systematically reviewed 60 articles (Marler & Boudreau, 2017) and 80 articles (Ben-Gal., 2019) about HR analytics respectively. Based on Ben-Gal (2019) studies, the researcher concluded that most research typically used one of four methodological approaches to examine their research question(s), namely empirical, conceptual, technical and case study-based approach. On top of that, Marler and Boudreau (2017) suggested that each research paper was addressing at least one of the following five areas of HR analytics, that is: (I) What is HR analytics (how has the concept definition evolved over time)? (II) Why does HR analytics work (what theories explain cause-effect relationships and consequences)? (III) How does HR analytics work (what are the processes)? (IV) What is required for HR analytics to produce ideal and accurate results? (V) What does HR analytics produce at the end (what are the outcomes)?.

The below section presents the current aspects of the relationships within its multifaceted view of HR analytics, it presents and explains how scholars and professionals define HR analytics. First of all, it is important to understand that the literature on how researchers examine HR analytics is relatively new, and many components, including the definition, are not well defined (Falletta & Combs, 2020; Marler & Boudreau, 2017; Van der Laken, 2018; Greasley & Thomas, 2020). Some researchers might simultaneously use “HR analytics” with “Artificial Intelligence” when discussing a topic (Giermindl et al., 2021). For example, a group of researchers from the Kennesaw State University, USA, defined HR analytics as a “systematic identification and quantification of the people drivers of business outcomes… using data mining and artificial intelligence to solve the HR analytics (people analytics) problems” (Liu et al., 2020, p.168). Similarly, Mishra et al. (2016, p.33) also proposed that HR analytics includes “statistical techniques, machine learning methods, and data mining models that analyse and extract existing and historical facts to make predictions” (Mishra et al., 2016). Moreover, a book titled “Artificial Intelligence for

HR" published by Eubanks (2019) and reviewed by the Chartered Institute of Personnel and Development (CIPD) also discussed HR analytics from the perspective of artificial intelligence.

On the other hand, some scholars might define the term more general from an HR standpoint (Hoffman et al., 2018; Lawler et al., 2004; Marler & Boudreau, 2017; Van den Heuvel & Bondarouk, 2017). For instance, Van den Heuvel and Bondarouk, (2017, p.4) defined HR analytics as "the systematic identification and quantification of the people drivers of business outcomes, with the purpose of making better decisions". The Economist Intelligence Unit and The Strategic Human Resource Management (SHRM) Foundation (2016, p.10) defined HR analytics as a tool that "uses statistical models and other techniques to analyse worker-related data, allowing leaders to improve the effectiveness of people-related decision-making and human resources strategy". Therefore, the present paper aims to reduce the inconsistency in HR analytics definitions and attempt to bring these definitions together in a meaningful way.

All in all, the objective is to provide readers with a more holistic perspective on what is HR analytics as presented in part 1:

1) **How to develop a more consistent definition of HR analytics and HR artificial intelligence.**

In relation to study two, this thesis will discuss and explore what factors influence the use of HR analytics. It is important to note that although the use of HR analytics seems to be a self-evident benefit to organizations, given the evidence that HR analytic approaches in HRM are paying off (Dahlbom et al., 2019; Guenole et al., 2017; Kryscynski et al., 2018; Levenson, 2011), comparatively few firms make use of it. Despite these benefits derived from HR analytics, recent literature argues that many firms are reluctant to make use of HR analytics because there are many factors that hinder or even prevent its use (Schiemann et al., 2018).

In particular, researchers pointed out that HR analytics needs to be embedded in an environment that has the structural and managerial capabilities to support the implementation of HR analytics (e.g., expertise or knowledge of HR managers to make use of the data and methods) (Angrave et al., 2016; Huselid & Jackson, 1997; Stone & Lukaszewski, 2009; Thompson & Heron, 2005; Vargas et al., 2018; Levenson, 2011). The legal regulations and managerial prerogatives also need to be in place for firms to collect, store and analyse data accordingly (e.g., HR analytics must be embedded in a business environment that has a well-developed structure, policy and management capabilities). In other words, organizations must not only have the knowledge and capability to make use of available data, but it also needs to have the right regulations in place for managers to perform analytics (Angrave et al., 2016; Bechter et al, 2021; Stone & Lukaszewski, 2009; Vargas et al., 2018).

Besides, researchers also found out that reluctance to share information between departments may also prevent managers from using HR analytics (Angrave et al., 2016; Dijk & Rothweilwe, 2016), as evidence suggested that departments tend to collect data that is beneficial for their own needs without much consideration for other departments. Furthermore, since the implementation of HR analytics is costly (e.g., return of investment (ROI) concerns) and requires to comply with direct data protection policies, such as the EU's General Data Protection Regulation (Burk & Miner, 2020; Webber & Zheng, 2020). Companies need incentives and motivations to leverage the use of HR analytics (e.g., the market factors or market pressures that motivate or even 'force' firms to do so) (Levenson, 2018).

Overall, this section of the thesis going to investigate the roles and relevance of a comprehensive list of factors that potentially explain why some firms make use of HR analytics while others refrain from its use. Specifically, it will systematically analyse the roles and relevance of firm-specific, i.e., *organizational, market-specific, and country factors* on the incidence of HR analytics using a multi-level framework. In effect, question two looks into evaluating the relationship between different factors and their interplay in the use of HR analytics in firms.

2) **What factors influence the use of HR analytics from a company perspective? Specifically, how does the complexity of HR systems and variable pay systems influence the use of HR analytics?**

In terms of study three, it will focus on the benefits of HR analytics. Specifically, it looks at whether the use of HR analytics and other variables can contribute to a company's financial performance. It is worth noting that although business professionals have suggested the benefits of using HR analytics, there is relatively little academic evidence available. The majority of the literature surrounding HR analytics predominantly focuses on how the HRM functions (i.e., in performance, work planning, recruitment and employee engagement) could take advantage of using HR analytics (Aral et al., 2012; Ben-Gal, 2019; Dahlbom et al., 2019; Eubanks, 2019; Hoffman et al., 2017; Levenson, 2011; Schiemann et al., 2018; Wang & Cotton, 2018) For instance, researchers explored on how HR analytics might enhance managers to identify people data patterns that may be difficult to observe, thus generating more tailored and accurate suggestions (Bronzo et al., 2013; Smith 2020). Evidence has demonstrated that recommendations from HR analytics are better than human judgments and assumptions. In particular, when it comes to predicting employee performance (Hoffman et al., 2017).

However, current research is insufficient to help decision-makers determine whether or not HR analytics actually brings benefits to organizations, and there are still significant research gaps in identifying and understanding the relationship between "HR analytics" and "business performance." Specifically, how HR analytics influences a company’s financial return. This part of the paper explores the role and relevance of a comprehensive list of factors that potentially influence a company’s financial return. The role and relevance of firm- and employee-specific factors on firm financial performance are systematically examined using an interaction effects analysis (i.e., variable pay system, HR analytics and employees’ motivation). Question three tests hypotheses about the relationship between different types of factors at different levels of analysis and their interaction with a firm's financial returns.

3) Does HR analytics have an impact on a company's performance?

Furthermore, in order to solidify our understanding of how HR analytics and HR artificial intelligence play a role in organizations, it is not only important to assess them from a quantitative perspective, but it is equally important to look at the qualitative aspects (i.e., to understand how HR analytics and/ or HR artificial intelligence influence organizations. These various aspects are often difficult to assess qualitatively). Therefore, following the quantitative analysis of study two and study three, a qualitative analysis will be presented. The purpose of the section is to better understand the connections or contradictions between qualitative and quantitative data. This allows researchers to explore different perspectives and uncover relationships that exist between the complex layers of the multi-layered research questions and facilitates different ways to enrich the evidence so that questions can be answered more thoroughly to solidify our understanding of how HR analytics and HR artificial intelligence work in organizations.

To summarize the search question section, Research Question 1 is designed to provide the reader with key information about HR analytics, while Study two examines how company characteristics affect the use of HR analytics. Study three, on the other hand, focuses on the benefits of HR analytics. Specifically, it examines whether the use of HR analytics and other variables can contribute to a company's financial performance. In addition, after the quantitative analysis, a qualitative analysis is presented to explore different perspectives and uncover relationships that exist between the complex layers of the multi-layered research questions.

2.0. Empirical evidence of HR analytics & HR artificial intelligence

The above paragraphs have been focusing on ideas and concepts around research questions. The following paragraphs will explore how HR analytics and artificial intelligence influence organizational performance such as recruitment, performance evaluation and employee's engagement.

2.1. Recruitment

In a study conducted by Hoffman et al., (2017), researchers were looking to evaluate employees' performance between computer recommendations (i.e., HR analytics) and manager selections. The results of the study showed that when managers override the computer's recommendations, employees end up performing worse than those selected from the computer. Therefore, Hoffman et al. (2017) suggested that when a manager hires against the recommendation of a computer, it is because of bias or error, not because of superior private information.

2.2. Performance

When it comes to how analytics can help companies perform better, Wang and Cotton (2018) provided a great example, particularly in improving the implementation of business strategies and human resources strategies. They used over 100 years of data from three major baseball online sources. The results of the analysis showed that team performance and players' social ties are positively correlated based on network closure theory and differentiated workforce theory. Based on this logic, Wang and Cotton (2018) suggested that companies should divide their employees into teams based on their own capabilities, in which employees can work closely together, strengthen their relationships with each other, and ultimately improve organizational performance (Wang & Cotton, 2018).

Moreover, Aral et al. (2012) used the principal-agent model and data from over 180 companies to examine whether IT software, pay-for-performance, and HR analytics can be effectively implemented separately or must be introduced as a tripartite system to gain a competitive advantage. Based on the results of the analysis, it revealed that IT software, HR analytics and performance pay are mutually correlated. Especially, management software implementation is associated with greater productivity premium when it is implemented as a system, but less beneficial when adopted in isolation (Aral et al., 2012).

As for artificial intelligence in human resources, it seems to offer more benefits than other traditional analysis methods such as statistical inference, regression analysis, Naive Bayes classifiers, etc. (Chui et al., 2018). The researchers studied a sample of more than 400 companies from 19 industries and nine business sectors and found that more than 270 companies could have achieved better performance if they had used artificial intelligence (Manyika et al., 2018).

Similarly, Chalfin et al. (2016) was examining how artificial intelligence can enable HR managers to improve recruitment and performance in the police and education sectors. In the case of the police force, the study analysed over 1,900 police officers who participated in 17 academic classes between 1991 and 1998. The researchers examined differences in police officer behaviour by comparing traditional hiring methods with hiring through artificial intelligence (Chalfin et al., 2016). The results of the analysis revealed that if police officers were to be selected by an artificial intelligence application, complaints could potentially reduce by 4.50%. Similarly, researchers suggested that by replacing the bottom 10% of teachers with average quality teachers through the use of artificial intelligence, the school could achieve better productivity (Chalfin et al., 2016).

Asano et al. (2015) used artificial intelligence (i.e., NLP technology) to evaluate more than 62,700 unsuccessful job applications and identified a list of comments and feedback that employers typically send to unsuccessful applicants.

Comments such as "too many applicants," "not enough experience," and "looking for other talents" were most commonly used by recruiters (Asano et al., 2015). In other words, evaluating the comments of unsuccessful applicants allows companies to understand their applicant pool and make appropriate changes.

In addition, the use of facial recognition has also enabled Dunne Group, a construction company, to automatically track and record employee check-in and check-out times (Aurora, 2016). This application of artificial intelligence was able to help the company prevent overpayments from absent workers by preventing a worker from signing in for someone else. Because construction is a team effort, each person may be allocated to different sites at different times. When thousands of workers are involved in a project, the software can not only track everyone's attendance but also reduce the time it takes to calculate each worker's wages (Aurora, 2016).

Last but not least, when it comes to recruitment and selection, companies often face information asymmetry and agency problems, and managers may rely solely on their own intuition or beliefs without considering the interests of the company (Stahl et al., 2012). With the right data, artificial intelligence not only has the ability to minimize managerial error, but it can also improve HR management efficiency and reduce the likelihood of any unconscious bias (HireVue, 2018; KPMG, 2019). For example, Unilever uses facial recognition in its recruitment process to analyse applicants' facial expressions in order to weed out candidates with undesirable characteristics (Nilsson, 2018). This artificial intelligence application enables Unilever to save more than £1 million and over 49,000 hours of work (HireVue, 2018; Nilsson, 2018).

2.3. Employee's engagement

There has long been an expectation that employee well-being would influence job performance (Bryson et al., 2014). Kukde (2017) used analytics to assess eight core emotions in a teamwork environment, namely anger, anticipation, disgust, fear, sadness, surprise, trust, and joy. The findings of the analysis suggested that the most frequently expressed emotions in teamwork are anticipation and trust. This actually reflects the fact that when a team experiences a high percentage of these emotions, everyone is motivated to trust each other and focus on the task, while a high percentage of negative emotions in a team affects employee productivity. (Kukde, 2017).

3.0. Data protection for both analytics and artificial intelligence

The sections above have focused on the benefits that HR analytics and HR artificial intelligence have for the business as a whole. But it is equally important to point out that managers must also consider data privacy when implementing HR analytics and HR artificial intelligence in organizations. Specifically, when organizations are increasingly leveraging the use of data to gain valuable insights from their employees, and data protection became an essential part of any organization. HR analytics and HR artificial intelligence both require employee data as input to generate findings, and organizations will have to store large amounts of this information on remote servers, which can also increase the likelihood of data loss.

Researchers suggested that hardware devices such as laptops, smartphones and even smartwatches could be interconnected with a company's database, which further raises the idea of privacy concerns and information security threats (Leenes, et al., 2017). For example, in 2014 cybercriminals stole over 100 million eBay customers' information by hacking into the eBay network (Estienne, 2014). In 2018, Facebook announced that nearly 50 million users were exposed to a security flaw within the data storage system (Lee, 2018). More recently, British Airways also announced that approximately 500,000 customers lost their personal data and credit card details because of a cyber-attack (BBC, 2019). As a result, researchers recommend that companies must conduct routine checks to ensure that data policies and procedures are being monitored correctly (Diez, et al., 2019).

In addition to the effort of organizations, the Europe Union has also taken the lead in data protection by introducing the General Data Protection Regulation (GDPR). The idea behind the new regulation is to ensure stricter requirements for consenting to the collection of people's data and strengthen the monitoring of data collection, control and evaluation. Employees and customers now have the right to object to their personal data being collected (European Commission, 2018; Jodka, 2018; Manyika & Bughin, 2018).

4.0. Additional Considerations: Big Data

When evaluating the purpose and role of HR analytics from an HRM perspective in this thesis, it is equally important to explain and understand what “Big Data” is. This is because big data and analytics go hand in hand, and both topics have a positive impact on each other. The availability of “Big Data” enables HR managers to improve the accuracy of decision making in the HRM function. This brief section presents the literature and considerations that form the perspectives and help answer the above research questions.

In the past 60 years of history of computer science, big data have never been the spotlight of any computer scientist. Algorithms and rules were always thought to be the most important element in making predictions (Russell & Norvig, 2016). However, with some recent research and developments in analytics, researchers came to believe that it would be more beneficial to focus on the data properties (e.g., volume, variety, velocity, and veracity), rather than the choice of algorithms (Russell & Norvig, 2016; Williamson, 2015). With the advent of the Internet of Things, social networks and smart mobile, big data processing offers new opportunities to explore information and data (Pundit & Rewari, 2018; Rocha, et al., 2019). In this way, cross-checking and predictive analysis can be performed in many areas (e.g., in business, science and the health care industry).

Multinational companies such as Apple, Amazon, Google and Facebook would all agree that using these digital footprints to make predictions have become an essential part of their daily operation (e.g., minimise uncertainty, consolidate decisions and increase productivity).

When it comes to defining what “Big Data” is. Angrave et al. (2016) suggested that “Big Data” could be referred to as any information that is in the form of heterogeneous, unstructured and too large for an ordinary database to store, control and analyse. For example, Anandarajan and Harrison, (2019); Eridaputra et al. (2014) and Grandinetti, et al. (2015) describe the phenomenon of big data that follows the concept of the Four V’s: Volume, Variety, Velocity, and Veracity.

Volume - In order to make accurate findings, analytics requires a large amount of data to analyse. Organizations are able to generate a vast amount of data from texting, tweeting, browsing and shopping. For instance, from an HRM perspective, management can gather and record all conversations in call centres between employees to customers, which enables HR analytics to improve the accuracy of findings.

Real-life example:

- Tesco generates more than 1.5 billion new items of data from customers every month (Manyika et al., 2011; Wamba et al., 2015), which indicates that their analysis would be more accurate compared to smaller competitors.

- Another great way to collect data is from social media users. Users send more than 245 billion emails and over 50 million tweets every day (PwC, 2015).

Velocity - Another important element of big data is velocity. It refers to real-time analysis and predictions. When organizations are able to gather a large amount of data, they also need to ensure that they can store and turn that data into insights. For example, HR managers can evaluate call centre employees' performance by combining speech recognition and real-time analytics processing.

Real-life example:

- A lot of the companies allocate resources to track data from their webpage to analyse their customers' and employees' behaviour in near-real-time (Manyika et al., 2011; Wamba et al., 2015). For instance, Amazon constantly updates customer delivery states, which also means Amazon's HR managers have the capability to evaluate employees' performance almost immediately.

Variety - Variety refers to how different types of data are processed when making business decisions. Because not all data would be stored in a single location. Therefore, if managers would like to consolidate a decision, it is advised that combining data collected from multiple sources would create greater efficiency and accuracy in decision making (Diez et al., 2019). For instance, when developing a training course for a team of employees, managers can combine

HR department data (i.e., employees' current performance) with marketing department data (i.e., consumers' interest and satisfaction) to predict each employee's performance after the training course.

Real-life example:

- Procter & Gamble (P&G) created a team of 100 analysts from different departments, ranging from marketing, sales, operations, supply chain and consumer research departments to evaluate the inter-relationships among different functional areas (Davenport, 2006; Wamba et al., 2015).

Veracity - In addition to the data volume, data velocity and data variety, organizations also need to consider data veracity. Data veracity refers to the trustworthiness of the data. Organizations need to be conscious about the type of data they are collecting, as data is often unreliable, imprecise and rather narrow. For instance, when making a bonus to employees, the HR department not only needs to evaluate employees' performance by assessing the line-manager feedback, but the HR department can also combine it with the sales data to consolidate their decisions.

Real-life example:

- eBay was suffering from data duplicate problems throughout its various database. Therefore, eBay developed an internal software tracking system to ensure all of the data are reliable and trustworthy (Davenport, et al., 2012).

5.0. Data Sources

The second part of this section will be looking at the data sources, namely private data, public data, ambient data, self-quantification data and community data (George, et al., 2014).

Private data simply refers to all data that are typically held by private firms and individuals. For example, during the recruitment process, managers often combine test scores and private information to select the best candidate (Hoffman et al., 2017).

Public data is owned by government organizations and local communities and is freely available to anyone (George, et al., 2014). Furthermore, ambient data are passively collected during everyday activities. These data typically have limited or no value when analysed alone, but once combined with other information, they can create new insights and value (George, et al., 2014). For example, the number of visitors and time spent on a particular recruitment site would fall into the stream of ambient data. This behavioural data provides new information about people's needs, wants, and intentions.

Self-quantitative data refers to data that an individual reveals by quantifying their behaviour and actions, such as smartwatches and wristbands (George et al., 2014). Last but not least, community data refers to unstructured data and information that can be used to predict patterns (George, et al., 2014). This type of data generally comes from Twitter feeds and online review platforms (George, et al., 2014). For example, when employees share their opinions about a company's work culture and benefits package.

Based on the illustration of the different types of data that can influence managers in their business decisions, it is clear that a variety of data types are required for accurate predictions in HR analytics.

6.0. Theoretical Framework

In HRM, performance management refers to the various elements companies face in defining, measuring and motivating employee performance in the hope of gaining a competitive advantage. It is encompassing several levels of analysis that are linked to the topics of Strategic Human Resource Management (SHRM) and performance evaluation (Den Hartog et al., 2004). The best way to answer the research questions is to understand the concepts of SHRM and High-Performance Work Systems (HPWS). However, before discussing each concept, it is important to be familiar with the Resource-Based View (RBV) as it is considered to be the backbone of SHRM (Colbert, 2004).

6.1 Overview of the Resource-Based View

The RBV literature has a history of nearly 40 years (Barney, 1986; Wernerfelt, 1984) and is based on the idea that a firm's success is the result of a mix of internal resources that create value and market characteristics that prevent the erosion of competitive value (Barney, 1991 Lazazzara & Galanaki, 2020). Researcher suggested that the “RBV has formed an integrating ground or backdrop for SHRM” (Colbert, 2004, p.341) because it provides a much-needed impetus for theory building in SHRM, in particular, it provides a framework for explaining how and why SHRM contributes to organizational performance by focusing on the importance of managing internal organizational resources for sustained competitive advantage (Bailey et al., 2018), linking HPWS to organizational success (Shin & Konrad, 2017).

RBV is one of the most widely used theories in the management framework that helps organizations achieve competitive advantage. It assumes that the relationships between organizational strategy, organizational performance, and internal resources (e.g., human capital) are closely interrelated (Barney, 1991; Spanos & Lioukas, 2001). Based on this idea with the HPWS concept, researchers proposed that the purpose for a company to adopt RBV is to invest in human capital so that organizations can create a competitive advantage (Patel & Conklin, 2012).

The RBV model also suggests that there is a range of resources in a company, including human resources, that could be combined to achieve a competitive advantage (Clulow et al., 2007). It focuses on promoting sustainable competitive advantage through the development of human capital, evaluating new ways to improve internal skills levels rather than acquiring new talents elsewhere (Clulow et al., 2007; Gandellini & Venanzi, 2012; Torrington et al., 2005). According to the RBV of strategic management, all tangible and intangible resources within a company can be combined to improve the chances of gaining a competitive advantage (Clulow et al., 2007). Tangible assets are resources that are in physical forms, such as land, machinery, and other business equipment. It is important to remember that all of these resources can be easily imitated and replicated by competitors. Therefore, it has been argued that it is almost impossible to maintain a company's competitive advantage if the organization relies heavily on tangible resources (Herzog, 2011; Poser, 2012).

On the other hand, intangible assets refer to all other resources that are not physically present but are owned by the company, such as human resources, corporate culture, experience, and reputation. These resources are much more difficult for competitors to imitate and replicate. For example, a company's reputation is built over a long period, and human capital recognizes that not every person is worth the same. Therefore, a firm's competitive position can be strengthened by leveraging a unique bundle of tangible and intangible resources that are determined by the firm's management (Wernerfelt, 1984). In other words, not all resources that a company possesses are of strategic importance. Only certain resources are capable of contributing to a value-creating strategy that puts the company in a position of competitive advantage. An organization's resources should aim to maintain the four characteristics that offer the potential for competitive advantage: valuable, rare, unique, and non-exchangeable (Beltrán et al., 2008; Lin & Wu, 2014; Torrington et al., 2005).

Valuable - The first characteristic is valuable, considering whether the resource adds value to the organization. In the context of HRM, Wright et al. (1994) suggested that employees are heterogeneous in their skills and that the supply of labour is also heterogeneous, making it a valuable resource for an organization to differentiate itself from other competitors. Based on this logic, the value of a resource (i.e., an employee) not only enables companies to take advantage of opportunities but also takes into account their ability to eliminate threats. In other words, it is about matching the right individual competencies with the right job role requirements, as each person makes a variable contribution to an organization and cannot be replaced (Talaja, 2012).

Rare – Rare resources are all resources that can only be obtained by one or a few companies. The competitive advantage resulting from the rarity of a resource is only temporary if competitors can replicate a similar resource. Researchers believed that a resource that is only "rare" or "valuable" cannot help a company gain a competitive advantage (Barney & Clark, 2007). It is important to clarify that this does not mean that a valuable resource, which is not rare, is unimportant to companies. Rather, these resources can help the company survive and compete in the marketplace (Barney & Clark, 2007). From an HRM standpoint, Torrington et al. (2005) also suggested that the most important competency of employees is their cognitive abilities. Since cognitive skills are normally distributed within the workforce, a person with higher levels of cognitive behaviours such as adaptability and flexibility at work would be considered a rare resource for the company.

Inimitable - Inimitable refers to a resource that is difficult or very costly for competitors to imitate or follow. When this applies in the HRM context, it considers how closely a competitor can imitate and determine a firm's competitive advantage from their exiting human resource pool (Wright et al., 1994). Researchers also believed that although some organizations may be able to replicate very closely their competitor's resources, each organization would have their own unique historical conditions such as company norms, culture and background (Torrington et al., 2005).

In addition, Barney (1995) has identified three reasons why resources can be hard to imitate, namely historical conditions, small decisions and social complex resources.

- Historical conditions refer to skills, abilities and resources learned from historical background. For example, Caterpillar's position in the heavy construction equipment industry would be difficult for competitors to imitate because Caterpillar was the U.S. Department of defence supplier during World War Two.
- The importance of numerous "small decisions" in the selection, development, and implementation of resources is relatively important in achieving competitive advantage. According to Barney (1995), a company's competitive advantage seems to depend on numerous "small decisions" in which the company's resources and capabilities can be used, developed, and deployed. He further proposed that a typical company has thousands of decisions to make every day, which means that competitors

are impossible to imitate by copying and learning.

- Socially complex resources refer to the resources and capabilities based on corporate culture, reputation, or interpersonal relationships (e.g., trust between employees and supervisors). These types of unique resources are much more difficult to imitate. Hewlett Packard (HP), for example, is known for having a supportive and encouraging culture in its industry. The company has managed to leverage this resource to its advantage, nearly doubling its market value without introducing radically new products or technologies (Barney, 1995).

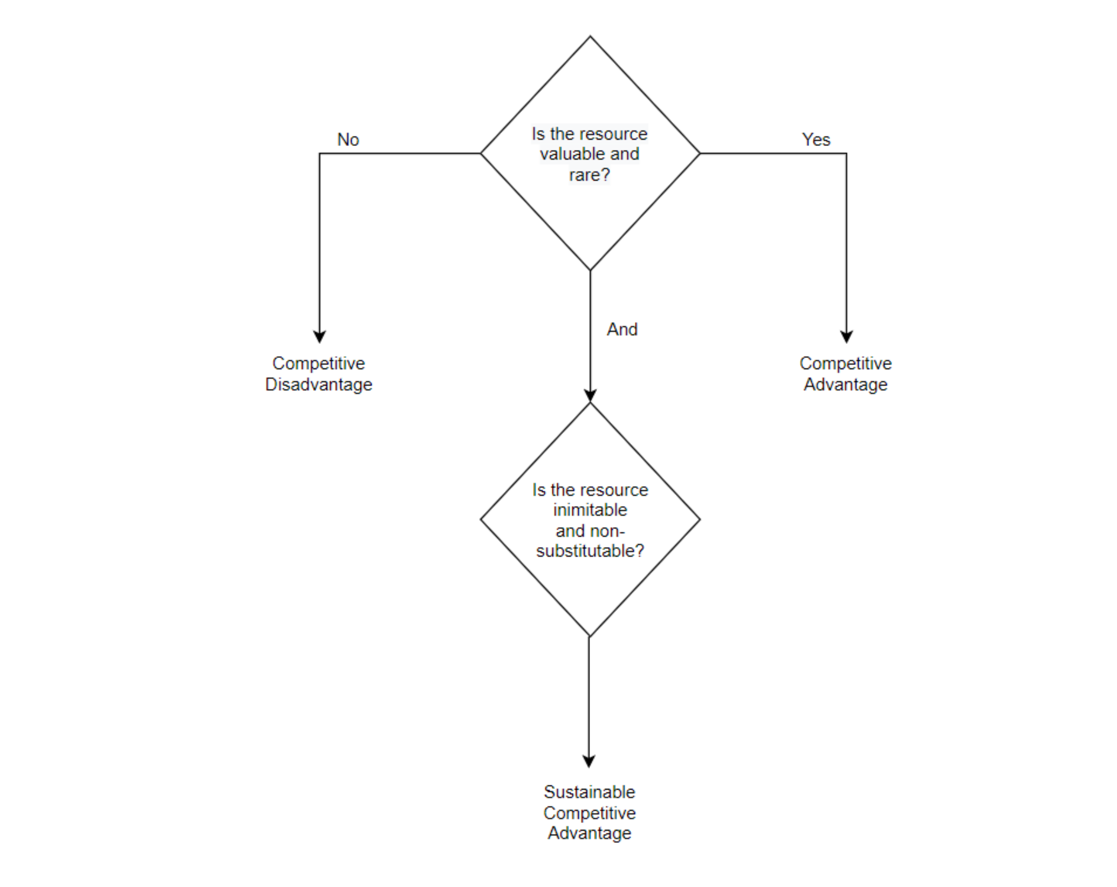
Non-substitutable - The final element is non-substitutable. It refers to any resource that cannot be replaced by another resource that is not rare. Wright et al. (1994) suggested that although a company may be able to substitute human resources with other resources (e.g., technology). However, in the long run, human resources can never be replaced with anything, as human capital does not become obsolete like other resources (Torrington et al., 2005).

Based on the VRIN model, it can be assumed that if a company can leverage technology such as HR analytics to obtain and achieve better HR functions, it can gain a competitive advantage. Moreover, most scholars also agree that:

1) An organization would be able to achieve a competitive advantage if the organization possesses and exploits resources and capabilities that are both valuable and rare (Eisenhardt & Martin, 2000; Mata et al., 1995; Newbert, 2008; Powell, 2001).

2) If these resources and capabilities cover all elements, valuable, rare, inimitable and non-substitutable, then the company will be able to maintain its competitive advantage (Eisenhardt & Martin, 2000; Mata et al., 1995; Newbert, 2008; Powell, 2001). Figure 1 shows whether a resource can help organizations achieve or even maintain a competitive advantage.

Figure 1: VRIN model flowchart



In addition, the RBV model assumes that an organization's resources, such as employee skills, abilities, and experience, will vary from organization to organization (Baier, 2008; Evans, 2014; Talaja, 2012). Management cannot use the exact same strategies to outperform the others. Instead, organizations must find the perfect combination of resources that work well within the organization to improve the chances of gaining and maintaining a competitive advantage. Moreover, the second assumption of the RBV is that all resources are immobile (i.e., do not move from one firm to another) and cannot be replicated by competing firms, at least over a short period (Baier, 2008; Evans, 2014; Talaja, 2012). Because of this inflexibility, firms cannot follow competitors' resources and implement the same strategy. The competition between Toyota and Ferrari is a good example of how two companies operating in the same industry and exposed to the same external forces and environments, but achieve different organizational performances due to different resources: Ferrari sells its products at much higher prices and consequently achieves higher profit margins. Toyota, on the other hand, does not follow the same strategy because it has different resources such as brand reputation, technology and human capital.

6.2. Research evidence of RBV

In a study published by Wu (2010), the researchers divided resources into two categories, namely VRIN and non-VRIN resources. For the VRIN resources, three variables were included, being management skills, specialized expertise, and alliance experience. While non-VRIN resources were measured by a single item: financial capital. Based on the results of the analysis, Wu (2010) suggested that when firms operate in low- and medium-volatility environments, the non-VRIN resources are positively associated with a competitive advantage, but when firms operate in high-volatility environments, only VRIN resources can help firms achieve competitive advantage.

Markman et al. (2004) conducted a study on how secure patents affect a firm's competitive advantage since patents are by definition considered valuable and rare. The results revealed that once the effects of past performance, firm size and investment in innovation are held constant, inimitability is significantly related to firm profitability and new product adoption. Non-substitutability, on the other hand, is only significantly related to new product introduction. Similarly, Newbert (2008) empirically studied over 115 companies in terms of their business processes between value, rarity, competitive advantage, and firm performance in a number of industries such as semiconductors, chemicals, electronics, computer equipment, and so on. The results of the analysis showed that value and rarity are related to competitive advantage and that competitive advantage is related to performance. Specifically, competitive advantage mediates the relationship between rarity and performance.

Furthermore, in a meta-analysis of 50 published studies, Liang et al. (2010) concluded that technology resources are likely to increase both external and internal capabilities, which in turn influence organizational performance. Organizational resources, including capabilities, organizational processes, organizational culture, information, and knowledge, have been shown to positively increase organizational effectiveness by influencing internal capabilities, thus the RBV model positively affects organizational performance.

6.3. SHRM and HPWS

The concept of SHRM was first formulated by Fombrun, Tichy, and Devanna in 1982 (Lengnick-Hall et al. 2009). In what is considered by many to be the first SHRM paper, Tichy et al. (1982) suggested that the role of an HR department is to improve organizational performance. Specifically, the researchers suggested that (I) HR activities have a significant impact on individual performance, (II) the cycle of HR activities is interdependent, and (III) in order to achieve effective SHRM, an effective HRM system is also required. Moreover, other researchers such as Baird and Meshoulam (1988); Fombrun et al. (1984); Beer et al. (1984); Evans (1986) and Wright and McMahan (1992) have also contributed to the field of SHRM. For example, in 1986, Evans suggested that SHRM has the potential to contribute to four strategic areas:

- the equality and human relations between employees
- the competitiveness compared to non-SHRM organizations
- the effectiveness in terms of innovation and flexibility to handle matters
- the relationships between business units and decentralized units within the company.

where Evans was one of the first researchers to recognize the need for a “balanced scorecard,” or dashboard, approach to assessing SHRM outcomes (Lengnick-Hall et al. 2009).

In other words, SHRM theory emphasizes the need for HRM strategies and HR practices to be developed within the context of overall business strategies and objectives (Armstrong & Baron, 2002; Nankervis et al., 2011). It is based on the assumption that SHRM considers the ‘macro’ perspective of the business (e.g., strategies and policies) and HR practices focus on the ‘micro’ perspective of the business (e.g., activities, functions and processes), in which relates to how managers would deal with HRM functions such as hiring, performance evaluation, reward, employment relationship, and development in the light of business strategy (Nankervis et al., 2011). The basic functions of SHRM, include human resources development, human resources evaluation and identifying the means and resources to be used in achieving decided objectives (Nigro et al., 2012).

Another theory worth including is the concept of HPWS. According to Messersmith and Guthrie (2010), HPWS can be defined as “a set, or bundle, of human resource management practices related to selection, training, performance management, compensation, and information sharing that are designed to attract, retain, and motivate employees” (Messersmith & Guthrie, 2010, p.242). Therefore, using a bundle of practices would lead to greater individual and organizational performance (Appelbaum et al., 2000; Becker et al., 1998; Delery & Doty, 1996; MacDuffie, 1995).

6.4. Choice of theories

According to Delery and Doty (1996), “the SHRM literature draws on three dominant modes of theorizing: universalistic, contingency, and configurational perspectives” (Delery & Doty, 1996, p.802), which will be adopted in this thesis to discuss the potential associated with HR analytics. This perspective is relatively important because adapting HR practices to the needs of specific contexts will be one of the determinants of whether HR analytics can be successfully implemented to support the needs of managers. For example, the universalistic approach suggests there is ‘one best way’ to manage employees to improve business performance. While the contingency approach and configurational theory believe there is no ‘one best way’ to manage an organization’s workforce. Organizations should therefore adopt a set of practices (i.e., HR analytics) that ‘fit’ with the organization’s choice of strategy (Delery & Doty, 1996; Gilmore & Williams, 2013; Powell et al., 2014).

By combining the idea of analytics and HRM. It would be interesting to see how the development of HR analytics would influence the concepts of SHRM and HRWS that were not previously available. In particular, it could provide a new and comprehensive way to assess the intermediary relationships through which they move and which are rationalized by their respective research questions.

Chapter 2: Study one – How to develop a more consistent definition of HR analytics and HR artificial intelligence.

1.0. Introduction

Human resource management is one of the most important functions in any business. It provides organizations with the ability to systematically engage and manage employees, maximizes employee performance and ultimately helps organizations to gain competitive advantages. With the advent of analytics and artificial intelligence in HR, companies are now able to gather data from a variety of sources. These technologies promise to improve business efficiency and productivity by predicting the likelihood of future events.

However, both researchers and evidence suggested that HR analytics and artificial intelligence in human resources lack a clear definition in literature (Gifford, 2019; Greasley & Thomas, 2020; Marler & Boudreau, 2017) and are often defined very vaguely. We believe that an unclear definition of HR analytics and artificial intelligence not only hinders development, but can also lead to confusion when discussing a particular topic. For instance, an unclear definition might increase the difficulty when developing regulatory mechanisms that ensure the effectiveness as well as the ethical acceptability of research on HR analytics and HR artificial intelligence (e.g., data protection on employee data). Therefore, this chapter will begin by divided into two sections, being HR analytics and HR artificial intelligence. For the former, it will present an overview of HR analytics, the different types of analytics techniques, and move into a discussion of how scholars define HR analytics while for the latter, it will present an overview of artificial intelligence, the potential side effects of implementing artificial intelligence and conclude with a discussion of how scholars define artificial intelligence. Overall, the contribution presents in this chapter aims to develop more consistent HR analytics and HR artificial intelligence definitions and attempt to bring these definitions together in a meaningful way.

As for the structure of this study. The study will first provide an overview of business and workforce analytics. Then, it will highlight the different types of analytics with their associated techniques and the data analysis cycle, followed by two working definitions on HR analytics and artificial intelligence in HR, before ending the chapter with a conclusion.

2.0. Overview of analytics

In general, analytics has been implemented in almost all sectors of business and government (e.g., healthcare, sports, and IT). It is a process of discovering, processing and examining different connections in data and providing users with meaningful information which may otherwise be hidden or overlooked (Mohr & Hürtgen, 2018). It is based on the idea that by evaluating large quantities of data using statistical models and pattern evaluations helps users streamline better decisions (Bronzo et al., 2013; Smith 2020). Camm et al. (2019, p.4) suggested that analytics is a tool that helps "decision making by creating insights from data, by improving our ability to more accurately forecast for planning, by helping us quantify risk, and by yielding better alternatives through analysis and optimization".

2.1. Review of literature in business analytics

Before we dive into what HR analytics is, it is important to remember that HR analytics is a subset of business analytics. Business analytics itself includes various forms of analytics, such as marketing analytics, supply chain analytics, financial analytics, and so on. For example, financial analysts often use analytics to assess the risk of a portfolio and the cost of a project, while marketers use analytics to predict customer behaviours in order to develop better marketing campaigns. In other words, analytics enable managers to combine different quantitative and qualitative data to create better scientific and evidence-based decisions (Kryscynski et al., 2018; Minbaeva, 2018). Companies such as Amazon, IBM, and Google have embraced analytics to solve some of the toughest problems in their organizations.

By looking at the above examples of analytics, we can see how business analytics has enabled different business departments to improve their efficiency and anticipate future events. Despite some delays in human resource management, some organizations have begun to realize the benefits of using HR analytics and are starting to follow the trend. Therefore, in today's challenging economy, HR analytics might be a key indicator in determining whether companies can outperform their competitors (Ben-Gal, 2019; Fulmer & Ployhart, 2013; Kapoor & Sherif, 2012).

3.0 Human resource analytics

Fundamentally, HR analytics is a tool that transforms data into HR topics, and it has a very similar purpose to all other applications of business analytics. Managers are looking to use HR analytics to reveal the hidden connections between various organizational dimensions (Houghton, 2019; KPMG, 2016), such as integrating employee performance with business value drivers (Becker et al., 2001; Van der Togt & Rasmussen, 2017) and business performance (Guenole et al., 2017). Managers may use some basic analytical approaches such as a simple data analysis or spreadsheet-based analytical model to examine the correlation and causation between variables. Alternatively, managers may adopt some sophisticated approaches such as simulation optimization analysis and rule-based analytical models to make better planning, evaluation and estimating risk for the organization (Angrave et al., 2016). A report published by Harvard Business Review also suggested that in general, HR analytics has six main purposes (Davenport et al., 2010): First, HR analytics can help managers to identify the key indicators of an organization's overall HR health, such as individual performance, turnover rate, employee engagement level and so on. Second, HR analytics can provide suggestions about which employees, departments, or teams need special attention when problems appear. Next, HR analytics can provide insight into employee retention levels at any given time (e.g., why do some employees choose to stay in the organization while some may decide to leave?). Fourth, HR analytics can determine which HRM actions have the greatest impact on the organization. Fifth, HR analytics can assist managers to decide when would be the best time to staff up or cut back on employee level. Lastly, HR analytics helps companies make decisions in real-time about employee-related demands. Therefore, managers can implement HR analytics along with other HR practices to improve HR performance, including workforce employment, rewards, employee development, talent management, and performance management. Prioritizing them in accordance using HR analytics can ensure more accurate results would be achieved. For example, Google uses HR analytics to analyse employees' characteristics to identify who has better leadership skills and communication skills from a group of people (Pattanayak, 2019), and Sysco, an American multinational corporation use HR analytics to keep track of employees' satisfaction levels has helped them save nearly $50 million in recruitment and training costs due to increase in retention (Davenport et al., 2010). Overall, HR analytics in its simplest form helps companies to monitor the efficiency and effectiveness of the HRM process.

3.1. Context

The literature surrounding HR analytics is at an exploration stage and more evidence may be needed to develop more comprehensive conclusions, numerous researchers have contributed to the topic by conducting an evidence-based review through an integrative synthesis of published peer-reviewed literature on HR analytics (Ben-Gal., 2019; Margherita, 2021; Marler & Boudreau, 2017). Researchers systematically reviewed 60 articles (Marler & Boudreau, 2017), 80 articles (Ben-Gal., 2019) and 68 articles (Margherita, 2021) about HR analytics respectively. Based on Ben-Gal (2019) studies, the researcher concluded that most research papers typically use one of the four methods to examine their research question(s), being empirical, conceptual, technical and case study-based approach. On top of that, Marler and Boudreau (2017) suggested that each research papers address at least one of the following five areas of HR analytics, that is: (I) What is HR analytics (how has the concept definition evolved over time)? (II) Why does HR analytics work (what theories explain cause-effect relationships and consequences)? (III) How does HR analytics work (what are the processes)? (IV) What is required for HR analytics to produce ideal and accurate results? (V) What does HR analytics produce at the end (what are the outcomes)?.

Furthermore, in developing relevant HR analytics practices in organizations, managers need to build specific skills and resources at the individual and organizational levels. These include an appropriate theoretical framework that makes connections between HRM, employee and organizational outcomes (Boudreau & Cascio, 2017; Levenson, 2018; Rasmussen & Ulrich, 2015), appropriate data and technology management (Minbaeva, 2018; van den Heuvel & Bondarouk, 2017), appropriate research and communication skills (i.e., storytelling) (Boudreau & Cascio, 2017; Ellmer & Reichel, 2021; Levenson, 2018; Minbaeva, 2018), and the strategic goals of using HR analytics should match the proximity to actual business problems.(Ellmer & Reichel, 2021).

3.2. Growth in HR analytics

With the widespread adoption of cloud-based systems, some organizations are beginning to invest heavily in different software programs to improve HR activities (Collins et al., 2017). There are three reasons why HR analytics is becoming more popular in the business world (Camm et al. 2019).

First of all, advances in data collection and digitization are more readily available than in the past. Researchers suggested that all interactions and performance in the business can now easily be obtained and recorded through social networks and internet traffic (e.g., employee-to-employee, manager-to-employee and manager-to-manager). These interactions between stakeholders generate a wealth of information for companies to analyse, enabling each company to understand and process data in a more systematic way (Soundararajan & Singh, 2016). The second reason is the power of computing and remote databases. The researchers believe that by having more control over the data, this allows managers to more easily explore and combine a large number of data sources (Raj, 2014; Trovati et al., 2015). Thus, providing a faster and more accurate result when making decisions. Last but not least, companies are now actively working on developing data methods to achieve better analysis and simulation algorithms (Camm et al., 2019). Therefore, all of the following reasons above provide the rationale for organizations to adopt HR analytics.

3.3. Adoption Trends

While the adoption of HR analytics is increasing, it is still relatively slow compared to other departments (Diez et al., 2019). In a report published by Deloitte in 2017, over 70% (10,000 HR and business leaders across 140 countries) of companies surveyed said HR analytics is a “high priority” in their organization. Yet only 9% of respondents believed they had a good understanding of which talent attributes would drive business performance (Collins et al., 2017; Deloitte, 2017; PwC, 2020), and over 79% of the HR professionals scored themselves as “low data analytics capability”, which is an alarming fact in an increasingly data-driven field (Diez et al., 2019). Moreover, recent literature also proposed that many managers are reluctant to use HR analytics because of a number of factors that impede their use (Schiemann et al., 2018). First and foremost, researchers pointed out that creating a data-driven culture where employees are highly motivated to learn new concepts is not an easy task. HR analytics must be embedded in an environment with structure, policy and management capabilities. This means companies not only need to have the knowledge and capability to leverage existing data, but they also need to have the right regulations in place for managers to collect, store and analyse it (Angrave et al., 2016; Stone & Lukaszewski, 2009; Vargas et al., 2018).

Secondly, the high implementation costs that companies must incur for HR analytics also discourage them from adopting this practice. For example, not only do companies have to consider the initial cost of the software, but they may also have to spend additional time and human resources to collect, store and analyse the data. Therefore, researchers suggested that HR managers need to involve other stakeholders in the decision-making process to successfully conduct HR analytics. This will ensure that the same specifications and guidelines are followed during data collection, allowing managers to make the analysis process more cohesive and efficient (Dijk & Rothweilwe, 2016). Besides, the HRM department is often forgotten or under-appreciated compared to other departments of the business, with analytics such as financial analytics, marketing analytics and operations analytics often being prioritized, which hinders the use of HR analytics (Angrave et al., 2016).

In addition to corporate culture, policies and skills, the analytical skills of HR professionals should also be mentioned. Angrave et al. (2016) proposed that the majority of HR professionals do not have enough knowledge and experience with data analysis. This idea is relatively important when examining the relationship between analytical skills and adoption rate in the business, specifically to evaluate whether HR managers with higher analytical skills would perform better in their role (Kryscynski et al., 2018). Researchers explored this question by analysing over 1500 HR professionals and employees, and conclude that those with higher levels of analytical abilities are expected to have higher job performance in general (Kryscynski et al., 2018). Similarly, Levenson (2011) investigated the differences between two HR positions, being analytics specialist and general executive in HR. The results were consistent with the view that a skills gap exists between the two positions. For instance, analytics specialists are often called upon for more advanced analytics tasks such as structural equations and correlation. Whereas general HR employees tend to handle more basic mathematical "analyses such as mean and percentage evaluation (Levenson, 2011). In a study published by Dahlbom et al. (2019), researchers surveyed nine Finnish companies that use HR analytics to manage their workforce. The results showed that the most common challenges that seemed to prevent HR professionals from advancing their ability to be data-driven were: lack of required skills, poor data quality in general, lack of business understanding, outdated IT infrastructure and systems, difficulty moving beyond reporting, and misconceptions about “Big Data” and its benefits for HR (Dahlbom, et al., 2019). Therefore, based on the above findings, it may explain why the adoption rate is lower in the HR industry (Angrave et al., 2016).

4.0. Types of analytics

When considering HR analytics as a subset of business analytics, it is important to recognize that both business analytics and HR analytics use the same analytic methods and techniques to perform analysis and propose solutions. Once companies have collected, extracted and classified all data, HR analytics methods are applied to search for useful information and hidden relationships. There are three types of analytics methods, namely descriptive analytics, predictive analytics and prescriptive analytics which are used in HR analytics (Camm et al., 2019; Duan & Xiong, 2015; Levine, 2013).

4.1. Descriptive analytics

When it comes to descriptive analytics, it is the most common type of analytics used by businesses (Appelbaum et al., 2017). It is a process that can be automatically used to look at historical data in context to understand the current state of affairs within an organization so that managers can make better decisions. In other words, the purpose of descriptive analytics is to determine the relationships between observations and evaluate past information to understand how each decision and result occurred (Duan & Xiong, 2015; Levine, 2013). It does not start with the business logic and apply the data, rather it follows the data to create the logic and explanation (Mueller & Massaron, 2016). For instance, when an organization's turnover rate is higher than the previous quarter, managers might be able to introduce better engagement programmes or employee benefits to motivate the current workforce.

4.2. Descriptive technique

Descriptive techniques include statistics reports, data queries, data dashboards, data mining and basic ‘what-if spreadsheet’ models (Camm et al., 2019). It is important to note that some of these techniques are used in conjunction with other analytics methods. For example, statistics reports and data mining can be combined with predictive analytics to estimate future events. All these methods assist managers to ensure that future planning is based on evidence history and not on management interest. By doing so, it can eliminate any assumptions, biases and agency problems that might cause by the managers (Mueller & Massaron, 2016).

Descriptive data mining is the use of analytical methods (e.g., correlation and cross-tabulation) to identify homogeneous groups, similarities and relationships that exist in data. Managers can use data mining to generate new information by analysing text, patterns and other variables on different networks such as Skype, Facebook, Microsoft Office, email and other text documents to evaluate how their employees are feeling about their role (Camm et al., 2019). In other words, descriptive data mining helps managers to describe the characteristics of the data in a targeted data set, hence improving organizations’ outcomes. It focuses on learning based on past experiences to do better in the future. For example, as an HR manager, he/ she can explore a candidate's browser history to understand and uncover patterns between roles and the candidate (e.g., why it took twice as long to hire for entry-level positions as it did for management positions in the past year?).

Data dashboards are another analytical technique that belongs to descriptive analysis (Levine & Stephan, 2014). They can be graphs, tables, maps, and charts. These methods visually present key performance factors for management to highlight the complex and complicated data in a simple visual format that truthfully represents and addresses the data. Daily dashboards might include a summary of sales by region, individual performance and staffing levels. Whenever there is new data available, managers can customize and display different information according to their department or company objective (Asllani, 2014).

Data querying is another method worth mentioning in the context of descriptive analytics and it is referred to as retrieving information or data from a database (Kozielski & Wrembel, 2009). The advantage of a data query is that it allows managers to efficiently select data based on characteristics. For example, instead of going through each employee's attendance record, HR managers can request and select a specific period (e.g., weeks, months, and years). The application then provides a descriptive summary of that event (e.g., all part-time employees who were absent from the New York office in July).

Unsupervised machine learning techniques such as clustering methods and association rules can be classified as descriptive analytics. Rather than following categorization or labelling, unsupervised machine learning aims to segment similarities in the data and predict the outcome by evaluating whether or not such commonality exists in the datasets (Kulkarni, 2017). These techniques are capable of learning on their own without human intervention to classify and produce the desired result (Etaati, 2019). The idea of unsupervised machine learning is best suited when the objectives require a large amount of data that is difficult to label, sorely relying on humans to labelling all data require too much time and resources. For instance, association rules can be used to evaluate employees' emails, Facebook and Twitter comments. In other words, by allowing the system to investigate large amounts of raw data, it can analyse and generate parameter values that replicate the idea of classification on its own. Thus, unsupervised learning would be best as a first step in the analysis, and managers could further examine the results if needed.

4.3. Predictive analytics

The goal of predictive analytics is to help managers answer and forecast the future, and it requires managers to input a large amount of data with high velocities to increase the accuracy of suggestions (Pundit & Rewari, 2018). For example, the question could be: 'What is likely to happen in the future if the company and the economic environment remain stable?' or, 'What is the success rate for new hires when the company increases compensation?'. In other words, this type of analysis method improves an organization's ability to predict employee performance and market changes, and helps anticipate change by combining various statistical methods to determine the probability of an event or outcome (Srinivasa et al., 2018; Stair & Reynolds, 2012).

4.4. Predictive technique

Simulation is an example of a predictive technique. It uses probability and statistics to construct a situation based on estimated data and information (Brown et al., 2013; Miller, 2014). It also enables managers to examine the impact of uncertainty for different scenarios. For example, organizations can use simulation models to assess the risks and benefits of introducing training programs for employees, allowing managers to use past data as a guideline to predict the gains and losses generated by training programs relative to the amount invested.

Predictive data mining has already been discussed in the section on descriptive analytics. But unlike its previous counterpart (i.e., descriptive data mining) where it looks at current and past conditions within a company, predictive data mining allows managers to predict the future, and it is commonly used to examine the likelihood of employees leaving the company (Nagadevara et al., 2008; Yang & Trewn, 2004; Yigit & Shourabizadeh, 2017). Moreover, when this idea is incorporated into machine learning, it can provide expected solutions by learning from a set of established data that contains some understanding of how the data was classified, labelled, and generated (Huang, 2017; Kelleher et al., 2015; Zander et al., 2005). For instance, if the goal is to automatically distinguish a high performer from a team. The user would need to input enough information to introduce the application with the explanation of what characteristics and qualities would classify as a high performer. By doing so, it can provide suggestions to managers whether a high performer is currently working in ‘Team A’, ‘Team B’ or ‘Team C’. In addition, predictive data mining methods also include methods such as classification, time series analysis, and regression (Abraham & Tan, 2010).

4.5. Prescriptive analytics

Last but not least, prescriptive analysis is the last method of HR analytics and is considered by researchers to be the most complex type of analysis, but one that provides the greatest benefit to the business (Šikšnys & Pedersen, 2018). It is an analytics method dedicated to find the best possible action plan based on different scenarios (Appelbaum et al., 2017; Holsapple et al., 2014; Srinivasa et al., 2018). Predictive analytics can continuously assimilate new data to re-forecast and re-specify a situation, thus improving the accuracy of forecasts and recommendations. In other words, the purpose of the prescriptive analysis is to help managers assess the impact of different possible actions and prescribe the best decision options to maximize the best possible outcome. (Camm et al., 2019; Lepenioti et al., 2020; Pyne et al., 2016). Unlike the previous two methods, where descriptive analysis aims to provide insight into the past, the predictive analysis provides predictions and forecasts about what might happen. Prescriptive analytics not only examines different options, recommends the best course of action and explains why this happens, but it also mitigates future risks and reveals the impact of each decision option (Jain, 2017). For example, LinkedIn uses optimization models to create recommendations for the best mix of companies or candidates to maximize the number of successful matches (Asllani, 2014).

4.6. Prescriptive technique

The main prescriptive technique is known as the optimization model, which is used to evaluate the optimal solution for the given constraints (Buglear & Castell, 2012; Minelli et al., 2013). For instance, financial analysts often use optimization models to determine the different combinations of investment products that yield the highest investment returns, while HR managers may use optimization models to select the best possible sources of recruitment strategy that both minimize costs and meet the requirements of business objectives. Another technique within prescriptive analytics is the simulation optimization model. This technique combines the use of statistics and probability rules to model uncertainty and enables managers to make better decisions in complex environments. Companies can develop a model to predict the probability that a department will become inefficient due to employee shortages. Assuming a company sets a probability of 0.4 as an indicator of operational inefficiency due to employee shortages, a human resources manager should begin hiring new employees as soon as the company reaches that value (Camm et al., 2019).

Another technique worth mentioning is reinforcement machine learning. Although this technique is not yet very developed in the HR environment, it is important to understand the logic behind it. Reinforcing machine learning is a behavioural learning model that follows feedback from data analysis to suggest the best possible solutions to users (Bonaccorso, 2017). This method is very different from the other two machine learning systems mentioned above. Instead of recognizing patterns and trends from the data sets, the system learns by trial and error, with learning based on a sequence of successful actions with the environment (Kulkarni, 2017). This kind of reinforcement machine learning would mostly apply in association with robots and driverless cars. For instance, when developers attempt to guide the robot up the stairs, the way the robot changes its balance and movement will be based on the results of its actions (Kaul, 2019). When the robot falls, the information will be stored and examined so that the next navigation step will be adjusted until the robot is fully capable of walking up the stairs. Similarly, developing a driverless car is complicated in many ways because there are too many unpredictable scenarios that could happen on the road. However, with the help of reinforcement machine learning, the algorithm can be optimized over time to find ways to deal with different situations.

4.7. Data analytics cycle

All in all, using HR analytics software or developing a system suitable for HR purposes requires iteration and proper planning. It would be unreasonable to expect HR analytics software to make accurate suggestions with unreliable data. Therefore, Hodeghatta and Nayak (2016) proposed the following business analytics cycle for companies to follow (Hodeghatta & Nayak, 2016). Table 1 provides an example of how these seven steps in analytics can be implemented with regard to HRM issues.

Table 1: Data analytics cycle

The seven steps of analytics	HR analytics scenarios
Understand the problem	An HR manager needs to identify the problem(s) with clear explanations as to why analytics can help with the situation. (e.g., high turnover rate).
Collect and integrate the data	An HR manager needs to collect all the necessary data, he/ she might need to integrate data from other departments to solve the problem.
Data cleansing	Once all the data have been collected, the HR manager needs to ensure the data are complete, correct, accurate and relevant.
Explore and understand the data	Explore and filter out any data that cannot be completed
Choose the right model techniques	At this stage, the HR manager needs to design which model technique would be suited for the design out with the mind that there is no one best way to generate findings. (e.g., regression analysis to predict the future).
Evaluate the model accuracy	After the model has provided some findings, HR managers need to ensure that the recommendations are sound and logical.
Ready to deploy	Now, managers can make use of the

	application.

5.0. HR analytics definition

The following section describes the current contexts in their multi-layered view of HR analytics, specifically outlining and explaining how researchers and practitioners apply and define HR analytics. First of all, it is important to understand that the literature on how researchers examine HR analytics is relatively new, and many components, including the definition, are not well defined (Falletta & Combs, 2020; Marler & Boudreau, 2017; Van der Laken, 2018; Greasley & Thomas, 2020). Some researchers might simultaneously use “HR analytics” with “Artificial Intelligence” when discussing such topics (Giermindl et al., 2021). For example, a group of researchers from the Kennesaw State University, USA, defined HR analytics as a “systematic identification and quantification of the people drivers of business outcomes… using data mining and artificial intelligence to solve the people analytics problems” (Liu et al., 2020, p.168). Mishra et al. (2016) also proposed that HR analytics includes “statistical techniques, machine learning methods, and data mining models that analyse and extract existing and historical facts to make predictions” (Mishra et al., 2016, p.33). Moreover, a book titled “Artificial Intelligence for HR” published by Eubanks (2019) and reviewed by the CIPD also discussed HR analytics with the perspective of artificial intelligence. On the other hand, other scholars might define the term as more general from an HR standpoint (Hoffman et al., 2018; Lawler et al., 2004; Marler & Boudreau, 2017; Van den Heuvel & Bondarouk, 2017). For instance, Van den Heuvel and Bondarouk, (2017, p.4) defined HR analytics as "the systematic identification and quantification of the people drivers of business outcomes, with the purpose of making better decisions". Economist Intelligence Unit and the Strategic Human Resource Management (SHRM) Foundation (2016, p.10) defined HR analytics as a tool that "uses statistical models and other techniques to analyse worker-related data, allowing leaders to improve the effectiveness of people-related decision-making and human resources strategy". Therefore, the following sections aim to reduce the inconsistency in HR analytics definitions and attempt to bring these definitions together in a meaningful way.

5.1. Examples of the definition of HR analytics

Examining the various definitions of HR analytics presented by scholars and practitioners allows for the identification of complementary perspectives and elements to consider in the field. Table 2 below presents a few definitions of HR analytics in chronological order.

Table 2: Few examples of commonly used definitions in the field of HRM
HR analytics is the use of statistical techniques and experimental approaches to show the impact of HR activities (Lawler et al., 2004).
HR analytics refers to "an evidence-based approach for making better decisions on the people side of the business, it consists of an array of tools and technologies, ranging from simple reporting of HR metrics all the way up to predictive modelling" (Bassi, 2011, p.16)
HR analytics is an indispensable capability, a strategic process that uses big data to enhance employees' value and broaden the strategic influence of the HRM function (CIPD, 2013).

KPMG (2013, p.4) defined HR analytics as “the synthesis of qualitative and quantitative data and information to bring predictive insight and decision-making support to the management of people in organizations”.
Van den Heuvel and Bondarouk, (2017, p.4) defined HR analytics as “the systematic identification and quantification of the people drivers of business outcomes, with the purpose of making better decisions”.
HR analytics is “an 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” (Marler & Boudreau, 2017, p.15).
Hoffman et al. (2018) refer to HR analytics as technologies that improve information symmetry between firms and managers. Reducing the impact of managerial mistakes or biases by changing how decision making is structured within the firm.
HR analytics is “a proactive and systematic process for ethically gathering, analysing, communicating and using evidence-based HR research and analytical insights to help organizations achieve their strategic objectives” (Falletta & Combs, 2020, p.53).
INFORMS defines “analytics as to the scientific process of transforming data into insights for the purpose of making better decisions” (Smith, 2020).
Walsh (2021, p.2) defines HR analytics is “the use of data collected on or about people within an organization to make better business decisions”.
Ellmer and Reichel (2021, p.2624) define “HR analytics as the situated, social activities of individuals and groups involved in HR analytics work with the goal to create knowledge relevant to decision-makers in organizations”.

After examining different definitions of HR analytics provided by scholars and practitioners, we believe that most of these definitions cover at least one of the following traits and that is: HR analytics (I) is a tool that improves the efficiency of decision making by managers. (II) is a systematic method for analysing and visualizing data for HR purposes. (III) is an evidence-based approach to employee-related matters. (IV) is a cross-process and cross-application endeavour with a wide range of potential impacts.

Similarly, in a paper published by Marler and Boudreau (2017), researchers also found several commonalities across HR analytics definitions. For instance, researchers suggested that HR analytics is not the same as HR metrics, but rather involves a more complex analysis of HR data that involves integrating data from various internal and external sources. HR analytics also involves the complex use of information technology to collect, process, and analyse data, and it involves supporting HR-related decisions. More importantly, HR analytics links HR decisions to organizational success and performance, which is the most compelling aspect of why HR analytics is so important and should be included in today's SHRM (Dahlbom et al., 2019; Marler & Boudreau, 2017).

After a systematic examination of the quality and meaning of the various definitions in the HR literature described above. HR analytics is generally understood to be more than just providing visual HR data reports to managers. HR analytics range from simple reporting of HR metrics all the way up to predictive modelling. A more coherent working definition of HR analytics considering all aspects of analytics has been developed based upon the INFORMS definition.

- **HR analytics** refers to the use of data and predetermined rules to perform analysis to identify useful information to improve management decision making. The focus is on using a varying combination of analytics techniques to improve organizational performance, from tracking information patterns with descriptive analytics, forecasting with predictive analytics, and developing recommended action plans with prescriptive analysis.

The new definition enables readers to identify and separate HR analytics and artificial intelligence from each other as evidence has suggested that there are some overlaps between the two terminologies (Liu et al., 2020; Mishra et al., 2016, Van den Heuvel & Bondarouk, 2017). HR analytics appears to enhance efficiency by connecting different HR practices and decisions, in which promotes a more strategic role than ever before.

6.0. Overview of artificial intelligence

Fundamentally, artificial intelligence is a very broad topic, as it covers various industries and functions, such as computer science, healthcare, and business. In simple terms, artificial intelligence could be referred to as "systems that display intelligent behaviour by analysing their environment and taking actions with some degree of autonomy to achieve specific goals" (European Commission, 2018b, p.1).

For this paper, it makes sense to look at artificial intelligence from a business perspective rather than from any other perspective. In the business environment, artificial intelligence helps companies accomplish their business tasks in two main ways. Firstly, artificial intelligence can handle standardized tasks through the use of automated business processes (ABP), which enable managers to operate their roles more effectively by reducing human intervention. For example, HR managers can use artificial intelligence chatbots to share some of their responsibilities, such as answering candidate inquiries, analysing workforce engagement and negotiating compensation. Similarly, the National Aeronautics and Space Administration (NASA) was also able to reduce its operational expenses by simply adopting ABPs throughout the organization (Davenport & Ronanki, 2008). A recent survey released by McKinsey also showed that nearly half of the companies surveyed have used artificial intelligence to improve their business operations (Manyika & Bughin, 2018).

Another common application of artificial intelligence in business is to identify patterns in data (i.e., data discovery), interpret the meaning of the data, and provide recommendations to managers for a given event, such as helping HR managers identify and predict turnover rates or create personalized job advertisements (Davenport & Ronanki, 2018). For example, General Electric (GE) used artificial intelligence to identify supplier data patterns, saving the company over $79 million by eliminating redundancies and negotiating contracts that were previously unavailable. Similarly, Deloitte reported that they experienced an improvement in their business performance through the use of artificial intelligence technologies (Davenport & Ronanki, 2008).

Although artificial intelligence can make predictions better than other traditional computer software, it is also important to remember that in order to take full advantage of artificial intelligence applications, companies must effectively combine employees' knowledge, datasets and processes together (Agarwal et al., 2018; Eubanks, 2019; McGovern et al., 2018). If any component is missing or of poor quality in any of the above elements, the accuracy of the entire prediction will be affected. Amazon, for example, had to halt its artificial intelligence recruiting tool in 2018 because it was revealed that there were problems in the data sets and algorithms against female applicants (Dastin, 2018).

6.1. Artificial intelligence application

In discussing the various types of artificial intelligence applications, it is important to remember that artificial intelligence is an umbrella term that encompasses different approaches to solving workforce problems (e.g., facial recognition, speech emotion recognition and natural language processing). These applications can improve the efficiency of HR managers and share some of their responsibilities that were previously unavailable. The following paragraphs describe each application that is commonly used in HRM.

6.2. Natural language processing

The early vision of natural language processing (NLP) was introduced in the 1960s, when computers were only able to understand the basic syntactic information and some key vocabulary in texts (Pundit & Rewari, 2018). However, with the increasing development of artificial intelligence, NLP is able to perform and understand the increasing complexity of human languages, such as the structure of sentences, the meaning of words, and the rules of conversations (Pundit & Rewari, 2018). For instance, NLP can now be used in the recruitment process to improve candidates' experience at every stage of the hiring process. (e.g., an automatic chatbot can be used to answer candidate questions before and after the interview). Moreover, applicant data such as resumes and interview test scores generally contain too many variables for recruiters to sift through in a short time. NLP can, therefore, quickly learn and sort through hundreds of applications based on different phrases, sentence structures, and other key components (Russell & Norvig, 2016; Spitzer et al., 2014), helping managers preselect candidates for recruitment.

Besides, NLP can also enhance work efficiency by offering a list of predetermined 'natural' responses for users (Eubank, 2019). For example, if an HR manager receives an email from a candidate that says, 'I just applied for a position at your organization and my resume is attached to this email', NLP would be able to offer predicted options such as, 'Great', 'Thank you for your resume' or, 'Thank you very much' for the manager to choose from, saving the manager's time in going through and responding to each candidate.

Another notable benefit is the idea of sentiment analysis (Deloitte, 2019; Eubank, 2019), where NLP can examine whether a document has a positive or negative tone and produce a summary of the document's key points. For example, HR managers would be able to determine the overall sentiment or mood of the workforce by analysing the organization's e-mail server (Eubank, 2019). Based on these results, organizations would be able to conduct appropriate consultations to resolve any issues that arise within the company.

In addition, when NLP is used in conjunction with speech recognition, the software is also able to understand human speech to handle more business tasks (Gary, 2016; Russell & Norvig, 2016). Researchers suggested that speech recognition is one of the key components of artificial intelligence (Gary, 2016; Russell & Norvig, 2016), where millions of people interact with speech recognition systems every day, from navigating mobile phones in voicemail systems or browsing the internet, all of which would involve some sort of speech recognition technology. In the HRM context, speech recognition has been applied in recruitment and employee engagement, specifically to determine employees' feelings about a situation (e.g., in a video interview or 360 feedback appraisal) (Diez et al., 2019). Moreover, employees with disabilities will also benefit from the use of speech recognition in their organizations. For individuals who are deaf, hard-of-hearing, arthritis and have repetitive strain injuries (RSI), speech recognition is used to automatically generate closed-captioning for conversations, effectively supporting employees with disabilities to have a better work experience, which was previously not feasible (Harper & Yesilada, 2008).

6.3. Facial and emotional recognition

By combining a camera, big data and algorithms, an application can be created to recognize and authenticate a person's unique facial structures and emotions (Baldauf & Stair, 2010). In other words, facial recognition technology is an artificial intelligence application that uses machine learning and human biometrics to identify a preselected individual from photographs or videos. Facial recognition systems can be used in a variety of ways. For instance, a government body may use facial recognition as access control in security systems. In a demonstration by the Chinese authorities, they were able to locate a targeted person in less than ten minutes (BBC, 2018). Eubanks (2019) on the other hand suggested that facial recognition can be adopted for HRM purposes. For example, some companies are using facial recognition for their payroll system with cameras that capture each employee checking in and out in front of the business building. When a person is absent, the system sends a notification signal to remind the HR manager to follow up on the situation. Furthermore, Facebook uses facial recognition software to tag people in pictures. At any moment when a person is tagged in a picture, Facebook will store all of the data about that person's facial structures, when the software has enough data about a person, it would be able to identify and tag a particular person's face without any human assistance. In 2014, Facebook claimed that its facial recognition system successfully matched the faces of millions of people with an accuracy rate of 97.35%, which was performed as good as humans with 0.18% differences, being 97.53% (Kumar et al., 2009).

In terms of recognizing emotions in an HRM context, emotion recognition technology allows HR managers to identify whether an applicant is excited, bored, confident, or honest when responding to questions in an interview (Diez et al., 2019). The application is able to prepare a report for managers detailing the emotional responses of job applicants with a rating scale indicating how "enthusiastic" or "nervous" the job applicant was during the interview process (Assad, 2019; Nilsson, 2018). In other words, if a manager is looking to recruit a curious person for the research and development team or a salesperson for the sales department, emotion recognition can provide an additional piece of evidence for the manager to rely on (Nilsson, 2018).

7.0. The dark side of artificial intelligence

No doubt that artificial intelligence brings many benefits to businesses. The above paragraphs have concentrated on the positive sides of artificial intelligence (i.e., how it can impact and enhance the potential of businesses and people). In the debate on the future of artificial intelligence, many experts believe many of these advanced technologies are logical and rational (Deloitte, 2019; KPMG, 2016), but as artificial intelligence becomes more complex and ubiquitous, there will inevitably be some negative impacts that are worth discussing. Many technologies, including artificial intelligence, might have some unintended negative effects. It is important to be mindful of finding the best way to properly manage artificial intelligence and to consider what consequences and negative effects might occur in the organizations. Researchers also emphasized that if the adoption of artificial intelligence creates more negative side effects than positive ones, then it would be only fair to navigate and redirect the effort elsewhere (Russell & Norvig, 2016). Therefore, artificial intelligence will not be able to live up to its promise unless it can establish confidence in its abilities. In this section, we will focus on the drawbacks and factors to consider when utilizing artificial intelligence.

7.1. Bias and Fairness

One of the most common concerns of using artificial intelligence is the idea of perpetuating bias (Eubanks, 2019). For example, during the U.S. presidential election, there were so-called ‘fake news’ appeared on many social media platforms. Because these platforms were previously programmed based on users’ preferences and habits, which directly related to the way how algorithms and/ or the data were used to train the artificial intelligence application, resulting in the technology-focused solely on users’ beliefs without checking the actual state of affairs. As a result, this might persuade peoples’ opinions and influence the outcome of the presidential election (Eubanks, 2019).

Similarly, in a study conducted by Caliskan et al. (2017), researchers also proposed that simply formatting artificial intelligence to follow ordinary human language would lead to human-like semantic biases: that is artificial intelligence would further deepen the idea of bias. Specifically, researchers found that artificial intelligence tends to associate positive terms such as ‘love’ to those who have a European-American name and unpleasant terms such as ‘ugly’ to those who have an African-American name during a pairing process. From a recruitment perspective, this might generate an unfair advantage for those candidates who have different characteristics and traits, such as having the different backgrounds, gender, ethnicity and education levels compared to the training dataset (Eubanks, 2019; Garth & Sterling, 2018; Hoffman et al., 2018).

Furthermore, this issue can also be seen in translation and labelling using artificial intelligence. When using Google to translate the following two sentences "o bir doktor" and "o bir hemşire" from Turkish into English. It will provide as "he is a doctor" and "she is a nurse" (Cox, 2018). However, the 'o' in Turkish is gender-neutral and does not specifically emphasise either male or female. Therefore, if a hospital uses such an application without mitigating the problem in filling positions in the medical field, it will lead to bias and unfair decisions (Cox, 2018). Furthermore, in 2015, Google mislabelled two black people as a gorilla due to the fact that the training datasets did not have enough black people pictures. In 2016, a U.S. organization also found that artificial intelligence tends to suggest that black people are twice as likely to be reoffended a crime than white people (Borgesius, 2018). Therefore, by looking at the example from above, it is important to remember that artificial intelligence inherently does not know the meaning of justice and fairness. Rather, it is sorely determined the suggestion that is based on the developer's instructions and data. Organizations, therefore, need to ensure that when programming on a robust and truly bias-free artificial intelligence application, it must include high-quality data sets to reinforce the power of artificial intelligence.

Overall, the relationship between the workforce and artificial intelligence is very complex (European Commission, 2018). On the one hand, artificial intelligence facilitates the way people interact and work, enhancing the development of organizations by expanding their capabilities and competitive advantages. But at the same time, facial recognition, neural networks, and speech recognition software are all developed by individuals and organizations, which might reflect individual values and social norms, and ultimately influence predictions. (Osoba & Welser, 2017). This is why it is so important for HR managers to validate any predictions generated by artificial intelligence, especially when it comes to interpreting employees' feelings and thoughts. (Diez et al., 2019).

8.0. Other concerns

Beyond the issues of bias and fairness concerns, artificial intelligence may also be used for undesirable purposes that cross society's ethical boundaries (Fazzin, 2019). For instance, a government might use artificial intelligence to monitor the behaviour of its citizens. Or, an unethical business might use artificial intelligence to scan and track employees' personal information. Researchers have also suggested that artificial intelligence chatbots such as 'Mgonz' and 'Natachata' have repeatedly tricked people into thinking that they are having a conversation with a real person (Russell & Norvig, 2016). Criminals can easily create a fake commercial website that looks identical to the site of the original, and use 'Mgonz' or 'Natachata' to steal people's personal information (Russell & Norvig, 2016; Nemati, 2013). In addition, in 2014 and 2015, Google and Samsung were criticized for having software preinstalled in their products that passively listened to and analysed users' conversations (Gray, 2016).

8.1. Unemployment concern

As artificial intelligence continues to grow, it is reasonable to assume that it may influence the job market and affect thousands of workers. Companies such as Goldman Sachs, Deloitte and PwC have also suggested that approximately one-third of the current U.S. workforce might lose their jobs because of artificial intelligence technology (Jennings, 2019). Specifically, if job roles require some sort of 'predictability', 'repeatability', or are data-driven, then these workers are likely to be replaced in the near future. For instance, Amazon already operates grocery stores where people can shop without sales clerks, which indirectly reduces job numbers (BBC, 2020). In addition, researchers also suggested if one day artificial intelligence becomes widely successful, it would at least pose a threat to lose the unique notion of being creative and innovative (Russell & Norvig, 2016; Weizenbaum, 1976).

8.2. Leisure time

Artificial intelligence is evolving so quickly that it can affect workers' free time. For example, there are more and more offices and businesses that are turning into 24-hour workplaces (Russell & Norvig, 2016). As a result, there is more pressure on employees to work more, which leads to employees having less free time and can even lead to mental health problems. However, researchers also pointed out that artificial intelligence, if used properly by companies, could also offer employees the opportunity to achieve a better work-life balance (Wisskirchen, et al., 2017).

8.3. Accountability and understanding

The use of an artificial intelligence system can lead to a loss of accountability and understanding. Imagine if a doctor relies on artificial intelligence to make diagnoses, but could not fully agree with the artificial intelligence's diagnosis. This might affect the doctor's judgement into thinking the artificial intelligence is more accurate than his expert knowledge (Torra et al, 2019), creating the 'black box' accountability and understanding problem. Similarly, HR managers might believe recommendations generated from artificial intelligence when forecasting HR matters such as employee retention, engagement and selection, which can lead to misallocation of resources that can potentially result in lost profits. Therefore, HR managers need to understand that artificial intelligence is only there to provide suggestions and it is not 100% accurate.

9.0. Artificial intelligence definition

After reviewing the drawbacks and benefits of using artificial intelligence, the following paragraphs will focus on the definitions surrounding artificial intelligence, which will first describe how computer science defines artificial intelligence and then move into examining how the enterprise defines artificial intelligence. This section aims to present a more coherent working definition for HR artificial intelligence and attempt to bring these definitions together in a meaningful way.

Firstly, some scholars acknowledge that it is difficult to define artificial intelligence (Burkhard, 2013; DeCanio, 2016) because there is no universally agreed definition of what natural intelligence is. From a computer science perspective, it has been suggested that artificial intelligence can be divided into four main areas, being 'systems that think like humans', 'systems that act like humans', 'systems that think rationally' and 'systems that act rationally' (Russell & Norvig, 2016). Researchers suggested that each of these four areas focus on evaluating computer intelligence and human intelligence in different ways. For instance, 'systems that think as humans' and 'systems that act as humans' measure the fidelity to human performance. Whereas 'systems that think rationally' and 'systems that act rationally' refer to an ideal performance measure (Russell & Norvig, 2016). Researchers further suggested that even though machines can clearly surpass human capabilities (e.g., playing chess, translating texts into multiple languages, looking for hidden patterns), artificial intelligence still cannot make ethical decisions or bring innovation and creativity toward new situations (Hislop et al., 2017). In other words, artificial intelligence may refer to the machine that has the capability to perform tasks similar to humans, but cannot fully mimic the way humans think under different situations that require more than just getting the right answer (e.g., ethical and moral behaviour) (Hengstler et al., 2016; Hislop et al., 2017; Siau & Wang, 2020). Because artificial intelligence is growing so rapidly, there has yet to be a single and agreed definition of artificial intelligence (European Commission, 2018).

To illustrate how scholars define artificial intelligence in computer science, a few examples have been selected in chronological order (see Table 3).

Table 3 : Definition of Artificial intelligence in computer science organized into four areas
Systems that think like humans - "The exciting new effort to make computers think . . . machines with minds, in the full and literal sense" (Russell & Norvig, 2016, p.2 cited Haugeland, 1985).
Systems that act like humans - "The study of how to make computers do things at which, at the moment, people are better" (Russell & Norvig, 2016, p.2 cited Rich & Knight, 1991).
Systems that think rationally - "The study of the computations that make it possible to perceive, reason, and act" (Russell & Norvig, 2016, p.2 cited Winston, 1992).
Systems that act rationally - Computational Intelligence is the study of the design of intelligent agents" (Russell & Norvig, 2016, p.2 cited Poole et al., 1998).

When it comes to defining artificial intelligence for human resource management, it is important to realize that 'HR artificial intelligence' is a subset of artificial intelligence. All of these definitions listed below underscore the role of artificial intelligence in replicating human behaviour, cogitation and thought, but at the same time, the term overlaps with the concept of HR analytics (see Table 4).

Some people may even associate ‘artificial intelligence’ with actual robots and machines, but rather ‘HR artificial intelligence’ focuses on the implementation of different applications to enhance HRM performance. For instance, NLP, facial recognition and artificial intelligence chatbot.

To illustrate how researchers and business professionals define artificial intelligence, this thesis have selected a few examples in table 4:

Table 4: Definition of Artificial intelligence in human resource management
“Artificial intelligence generally refers to the ability of machines to exhibit human-like intelligence, for example, solving a problem without the use of hand-coded software containing detailed instructions” (Bughin et al., 2017, p.7).
“Artificial intelligence refers to the technology used to do a task that requires some level of intelligence to accomplish, a tool trained to do what a human can do” (McGovern et al., 2018, p.1).
“If a computer can perform a task that a human could perform, that falls somewhere on the spectrum of artificial intelligence” (Eubank, 2019, p.30).
“Artificial intelligence refers to the ability of computer systems or machines to display intelligent behaviour that allows them to act and learn autonomously. Artificial intelligence takes data, applies some calculation rules (or algorithms) to the data and then makes decisions or predicts outcomes” (Marr, 2019, p.4).
“Artificial intelligence refers to the ability of a machine to learn from experience, adjust to new inputs and perform human-like tasks” (Duan et al., 2019, p.63).
Artificial Intelligence can be defined as “the development of computers to engage in human like thought processes, such as learning, reasoning, and self-correction” (CIPD, 2020, p.5).

A working definition emphasizes the concept of automation, which is identified as the distinguishing theme between HR artificial intelligence and HR analytics. For example, Eubanks (2019) proposed that some companies are using HR artificial intelligence (e.g., facial recognition) to automatically calculate employee attendance for their payroll system, whilst other researchers also suggested that HR artificial intelligence such as artificial intelligence chatbots and NLP can be utilized for recruitment automation (Russell & Norvig, 2016; Spitzer et al., 2014).

Therefore, we propose the following working definition when evaluating the qualitative part of the sections.

- **HR artificial intelligence** refers to the ability of computer systems or applications to support and manage HR decisions, where the system can automatically improve and handle HRM functions. For example, by using sentiments analysis to enhance the hiring decision or using natural language processing to ensure that job advertisement that is free of unconscious bias.

10.0. Conclusion for study one

In summary, HR analytics and artificial intelligence have become the strategic importance of the HR domains in recent years (Ben-Gal, 2019; Eubank, 2019; Manyika & Bughin, 2018; Marler and Budreau, 2017; Rasmussen and Ulrich, 2015). More and more organizations are beginning to realize that human capital is an important organizational asset that needs to be managed appropriately (Ben-Gal, 2019; Bontis and Fitz-enz, 2002). The realization of the potential benefits from software technologies, such as HR analytics and HR artificial intelligence, as well as the availability of HR data generated from multiple sources, are driving the use of these new advanced technologies to improve HR functions (Eubanks, 2019; Huselid, 2018; Marler & Boudreau, 2017; Nilsson, 2018; Strohmeier, 2020).

This chapter has successfully provided a current snapshot of HR analytics and HR artificial intelligence. It highlights how HR analytics and HR artificial intelligence can be used to stimulate productivity, business performance and enhance managers' decision-making. Specifically, after systematically examining the quality and meaning of the different definitions in the HR literature described in chapter 2. The author believes that HR analytics is usually considered more than just providing visual HR data reports to managers. HR analytics ranges from simple reporting of HR metrics all the way up to predictive modelling. Specifically, most of these definitions provided in chapter 2 cover at least one of the following traits. For instance, HR analytics a) is a tool that improves the efficiency of managers' decision making. b) is a systematic way to analyse and visualize data for HR purposes. c) is an evidence-based approach to employee-related matters d) is a multi-process and multi-application endeavour with a broad spectrum of potential impacts (Margherita, 2021). Therefore, a more coherent working definition of HR analytics considering all aspects of analytics has been developed based upon the INFORMS definition (Smith, 2020): "analytics as the scientific process of transforming data into insights for the purpose of making better decisions".

Therefore, we propose the following working definition:

- **HR analytics** refers to the use of data and predetermined rules to perform analysis to identify useful information to improve management decision making. The focus is on using a varying combination of analytics techniques to improve organizational performance, from tracking information patterns with descriptive analytics, forecasting with predictive analytics, and developing recommended action plans with prescriptive analysis.

The working definition allows readers to distinguish between HR analytics and artificial intelligence, as there is evidence of some overlapping between the two terminologies (Liu et al., 2020; Mishra et al., 2016, Van den Heuvel & Bondarouk, 2017). HR analytics appears to enhance efficiency by connecting different HR practices and decisions, which promotes a more strategic role than ever before.

When it comes to defining artificial intelligence for human resource management, it is important to recognize that "artificial intelligence in human resource management" is a subset of artificial intelligence. During the development of the working definition in this paper, we examined various definitions of artificial intelligence from both a computer science and human resources perspective and found that artificial intelligence can be divided into four main areas, being ‘systems that think like humans’, ‘systems that act like humans’, ‘systems that think rationally’ and ‘systems that act rationally’ (Russell & Norvig, 2016). A working definition that emphasizes on the concept of automation, which is identified as the distinguishing theme between HR artificial intelligence and HR analytics. Therefore, we propose the following working definition.

- **HR artificial intelligence** refers to the ability of computer systems or applications to support and manage HR decisions, where the system can automatically improve and handle HRM functions. For example, by using sentiments analysis to enhance the hiring decision or using natural language processing to ensure that job advertisement that is free of unconscious bias.

Chapter 3: Study Two – What firms' characteristics influence the use of HR analytics

1.0. Introduction

There has been an ongoing discussion focusing on the strategic roles of analytics in the HRM industry (Aral et al., 2012; Marler & Boudreau, 2017; Mittal & Gujral, 2020; Oracle, 2019; Tambe et al., 2019). As technologies continue to advance, HR professionals have increasing access to new sources of structured and unstructured data that allow them to better analyse the complexity of workforce-related decisions (Beath et al., 2012). Specifically, looking at how HR analytics can enhance the idea of HR functions, that is, the long-term goals of the organization can be achieved with the help of new technology to measure and understand employee behaviour with unprecedented accuracy (Dahlbom et al., 2019). With its importance in today's data-driven economy (Cavanillas, 2016), and the growing recognition of the potential benefits of HR analytics (Ben-Gal, 2019; Dahlbom et al, 2019; Ledet et al., 2020). This chapter will first put a spotlight on the idea of Strategic Human Resource Management (SHRM), particularly with regard to the High-Performance Work System (HPWS) and each of the perspectives, such as the universalistic theory (i.e., best-practice), the contingency theory (i.e., best-fit) and the configurational theory. Follow by the research question hypotheses, methodology, results findings, discussion and conclusion.

2.0. Overview of Strategic Human Resource Management

Given the growing importance of human resources in organizations, SHRM has never been more important than now (Armstrong & Baron, 2002; Boxall, 1996; Hendry & Pettigrew 1986; Paauwe & Boon, 2018; Wright et al., 2005). In order to gain maximum effect from HRM, SHRM theory emphasizes the need for HRM strategies and HR practices to be developed within the context of overall business strategies and objectives (Nankervis et al., 2011). It is based on the assumption that SHRM considers the 'macro' perspective of the business (e.g., strategies and policies) and HR practices focus on the 'micro' perspective of the business (e.g., activities, functions and processes), which relates to how managers handle HRM functions such as hiring, performance evaluation, reward, employment relationship, and development in the light of business strategy (Nankervis et al., 2011). SHRM goes beyond the functional concept of HRM by considering other elements such as matching resources to the present and future objectives of organizations, employment relationships, and structure and culture changes (Agarwal, 2008). In general, SHRM is concerned with employee problems and practices that are related to or affected by the organization's strategic plan. The main objectives of SHRM are: (I) to provide all of the necessary elements to motivate employees in the organization to achieve sustainable competitive advantage. (II) To ensure both the organization and the needs of employees are met by developing and implementing HR practices (e.g., HR analytics) that are consistent with the business strategy (Agarwal, 2008; Strohmeier, 2009).

In order to fully understand how HR analytics might influence SHRM, it is important to define and understand the idea of SHRM. One of the best-known definitions was proposed by Wright and McMahan (1992, p.298), who described SHRM as “the pattern of planned human resource deployments and activities intended to enable an organization to achieve its goals.” While, Bagga and Srivastava (2014, p.2) refer to SHRM as the “linking of human resources (HR) with organizations’ strategic goals and objectives so as to improve business performance and develop organizational culture that nurtures innovation, flexibility and competitive advantage. linking of human resources (HR) with organizations’ strategic goals and objectives so as to improve business performance and develop organizational culture that nurture innovation, flexibility and competitive advantage”. Hendry and Pettigrew (1986) suggested that there are four components that make the SHRM ecosystem, which include:

1. The use of planning in human resource management
2. An integrated approach to the design and implementation of HR systems
3. Matching HRM policies and activities with the business strategy of the

company

4. Viewing people as a strategic resource for the achievement of "competitive advantage"

In addition, Armstrong and Brown (2019, p.8-9) made it clear that SHRM is "the overall approach that provides guidance on how key issues of human resource management can be dealt with strategically so as to best support the achievement of corporate goals".

3.0. HPWS and evidence

The concept of HPWS is a human resource approach that gained substantial academic attention in the mid-1990s (Pfeffer, 1998; Wilkinson et al., 2014). In some cases, this approach may also be referred to as the 'best-practice HRM' approach (Marchington and Wilkinson, 2002), the 'high-involvement HRM' approach (Wilkinson et al., 2016) or the 'high-commitment HRM' approach (Gould-Williams, 2004). In fact, the main concept behind all of the terminologies is defined as "a set, or bundle, of human resource management practices related to selection, training, performance management, compensation, and information sharing that are designed to attract, retain, and motivate employees" (Messersmith & Guthrie, 2010, p.242). Therefore, results in greater individual and organizational performance (Appelbaum et al., 2000; Becker et al., 1998; Delery & Doty, 1996; MacDuffie, 1995). By following the concept of HPWS, employees are more likely to be committed to the organization, enjoy greater autonomy to develop relevant skills, and assist organizations in achieving higher productivity (Appelbaum et al., 2000; Guthrie, 2001; Tomer, 2007). HPWS views employees as the reason for organizations' competitive advantage, rather than as a typical source of expense.

Logically, the term HPWS makes the assertion that there is a system of work practices that in some way leads to better organizational performance. There are three concepts explicitly embedded in this assertion: "Performance", "Work Practices", and "Systemic Impact". To understand what is meant by a HPWS, we need to examine each of these concepts in turn. For example, the "systemic impact" is well established in the HPWS literature reviews (e.g., Dyer and Reeves, 1995; Becker and Gerhart, 1996; Delery and Shaw, 2001). According to MacDuffie (1995: 200), the "bundling" of work practices in HPWS is crucial: "It is the combination of practices into a bundle rather than individual practices that shapes the pattern of interactions between managers and workers." The same claim is made by Ichniowski et al. (1997) and Appelbaum et al. (2000), who argue that productivity gains are greater when firms adopt systems of complementary practices. Therefore, we believe that the importance of selecting one practice to form a bundle of practices can lead to confusion and complexity. Therefore, it would be reasonable to assume that this problem can be better addressed through the use of technologies such as HR analytics.

In addition, a research paper published by Boxall and Macky (2009). In it, the researchers propose that HPWS is about "systems of practices" where organizations could achieve higher productivity gains if managers adopt and select systems that complement each other (Appelbaum et al., 2000). More specifically, organizations could use HPWS as a "competitive system" (Batt, 2002, Boxall, 2003) to outperform other competitors and increase employees' cognitive and motivational satisfaction (Vandenberg et al., 1999). Some scholars see benefits to both parties (e.g., Appelbaum et al., 2000), while others question the benefits to firms (e.g., Cappelli & Neumark, 2001; Way, 2002) or to workers (e.g., White et al., 2003), and some rightly question the value to both parties (e.g., Godard, 2004).

Besides, one of the most compelling pieces of evidence regarding the link between SHRM implementation and organizational performance is provided by Professor John Purcell and his colleagues at the University of Bath for the CIPD. (Armstrong & Brown, 2019). In their longitudinal research, Professor Purcell and his colleagues concluded that there is a positive relationship between positive attitudes to HR policies, practices, levels of satisfaction, motivation, commitment and operational performance (Armstrong & Brown, 2019). Similarly, Huselid and Becker (1997) examined over 700 firms with regard to the impact of the presence of HPWS and its effectiveness and alignment with firms' competitive strategy on the shareholder. The results of the analysis support the assumption that HPWS has an economically positive and significant impact on business performance.

A study conducted by Kling (1995) revealed that when organizations introduced formal training programs to their employees, organizations typically experience a

19% increase in productivity compared to their counterparts. Moreover, researchers also revealed that there is a roughly 20% decrease in time in manufacturing products when organizations implement gainsharing practices. Similarly, Appelbaum et al. (2000) interviewed nearly 4,400 workers in more than 40 manufacturing facilities to evaluate the impact on HPWS (e.g., plant performance). The results of the study showed that through collaboration and training, workers greatly accelerated their manufacturing process and were able to meet consumer demand for faster delivery time.

Macky and Boxall (2007) used national employee survey data to examine how the process of using HPWS practices would foster employee emotion and engagement. Researchers found that the commitment created by HPWS is causally flowing through the mediating effects of employee-level job satisfaction and trust in management (Macky & Boxall 2007). Moreover, a study published by Garcia-Chas et al. (2014) examined the perceptions of more than 150 employees from 19 different companies on HPWS and various mediating variables. Researchers found that HPWS is positively related to job satisfaction, procedural justice, and intrinsic motivation. However, only job satisfaction mediated the relationship between HPWS and retention, while intrinsic motivation and procedural justice mediated the relationship between job satisfaction and HPWS.

Besides, Veth et al. (2019) used data from more than 1,500 employee surveys to examine (I) the relationship between perceived availability and use of HRM practices and employee outcomes (i.e., job engagement and employability), and

(II) how employee age moderates these relationships. The results suggested that HRM practices related to learning, development, and incorporation of new tasks may be positively associated with work engagement and employability. However, the results also revealed that age does not change or experience a significant moderating effect on the relationship between HRM and employee performance. (Veth et al., 2019).

Furthermore, Khatri (2000) used over 190 largest companies in all major industries in Singapore to examine the relationship between ‘HR practices and business strategy’ as well as ‘HR practices and company performance’. The results of the study revealed that overall business strategy directly affects HR practices, which in turn affects firm performance. Thus, business strategy has a moderating effect on the relationship between HR practices and organizational performance (Khatri, 2000).

Other studies also have illustrated that there is a positive correlation between HPWS and business performance (Guthrie, 2001; Wright et al., 2005). For instance, productivity with business performance (Ichniowski et al., 1997) and employee retention levels with business performance (Arthur, 1994; Huselid, 1995). Besides, Combs et al. (2006) conducted a meta-analysis of more than 90 contemporary research studies on the basis of the HPWS-performance relationship. The results also indicated that when the standard deviation of the use of HPWS increases by one, it leads to a 4.6% increase in return on resources, and a 4.4% decrease in turnover (Paracha et al., 2014).

Although it might be reasonable to assume that HRM practices and organizational performance are correlated according to various studies. (Appelbaum et al., 2000; Armstrong et al., 2010; Bae & Lawler, 2000; Batt, 2002; Birdi et al., 2008; Collins & Smith, 2006; Collings et al., 2010; Combs et al., 2006; Datta et al., 2005; Delaney & Huselid, 1996; Delery & Doty, 1996; Guthrie, 2001; Huselid, 1995; Kim & Wright, 2011; Lee et al., 2012; MacDuffie, 1995; Purcell et al., 2003; Sun et al., 2007; Youndt et al., 1996; Way, 2002). However, some studies do also show that there is a contradiction when looking at the concept of HPWS (Malizia et al., 2017; Ogbonnaya et al., 2016). Kroon et al. (2009) argued that HPWS does not provide the same mutual benefits to workers and employers (i.e., mutual benefit - employees enjoy greater job flexibility and better compensation plans, and employers benefit from higher productivity and greater employee retention). Researchers suggested that the additional productivity and business performance achieved through HPWS is the result of requiring employees to work harder and handle heavier workloads (Kroon et al., 2009). Similarly, this view is supported by Godard (2001), who studied more than 500 employees in Canadian companies that have implemented HPWS, and found that high-performance practices are strongly associated with intrinsic rewards, but also cause higher levels of stress and anxiety among employees.

In addition, researchers have suggested that the relationship between HPWS and performance is influenced by the “black box” of HR practices, particularly within the methodology (Fleetwood & Hesketh, 2010; Paauwe, 2009; Purcell et al., 2003). While it is possible to make empirical observations when utilizing HR practices (input phase) and measuring company performance (output phase), it can be difficult to determine through research what is happening between these two phases. (i.e., would the company have produced the same results if it had adopted the same HR practices?)

The sections above focused on concepts related to SHRM and HPWS. Specifically, it provided an overview of HPWS and explored how HPWS can potentially create a competitive advantage for organizations, as well as the concerns associated with HPWS. The following paragraphs will explore the “best-practice” approach (universalistic theory), the “best-fit” approach (contingency theory) and the configurational theory, and their relationship with HR functions.

3.1. The Universalistic Theory

Universalistic is “the simplest form of theoretical statement in the SHRM literature because they imply that the relationship between a given independent variable and a dependent variable is universal across the population of organizations” (Delery & Doty, 1996, p.805). The link between company performance and the “best-practice” is well documented in HRM theory (Gilmore & Williams, 2013; Kaufman & Miller, 2011; Sirmon & Hitt, 2009; Vlachos, 2009). There is a long list of HR practices that can be combined to influence company performance (Armstrong, 2006; Kintana et al., 2006; Vlachos, 2009). There is a perception that there is ‘one best way’ to manage employees in order to improve business performance. It is worth noting that the idea of the universalistic theory (i.e., best-practice approach) does not yield any synergy effects between the HR practices, but rather considers that they are additive (Lertxundi & Landeta, 2011). It is therefore based on the assumption that the more HR practices are implemented, the better results a company can achieve. The hypothesis proposes that HR practices would impact linearly on organizational performance, such as employee knowledge, productivity and economic success.

In addition, it is important to remember that there is no agreement on a single set of HR practices that can guarantee to achieve the same level of performance (Wilkinson et al., 2016). For instance, Terpstra and Rozell, (1993) proposed that there are five recruitment practices that could be adopted to improve organizational performance (Terpstra & Rozell, 1993). In contrast, Pfeffer (1998) suggested that there are exactly seven practices that guarantee an organization to gain a competitive advantage regardless of the environment or industry in which the firm operates (Redman & Wilkinson, 2002; Malik, 2018; Price 2007). Moreover, one manager may select one practice while others may not. For instance, Huselid (1995) believed that 'variable pay' practice is the core focus of HPWS but Arthur (1994) believes otherwise. Despite the differences in identifying all of the desired indicators. The "best-practice" would generally include, careful selection, training, mentoring, incentives, knowledge-sharing and other shared decision-making mechanisms.

3.2. Evidence of the Universalistic Theory

In general, many researchers would agree that the use of “best-practice” can enhance business performance (Delery & Doty, 1996). For example, Terpstra and Rozell (1993) proposed that certain recruitment practices, such as structured interviews, validation and cognitive tests are positively related to a firm’s profitability. Similarly, Gerhart and Milkovich (1990) found that companies that included contingent pay systems in their HR practices (i.e., rewards and compensation policy) performed better financially. Leonard (1990) has also shown that companies that use long-term incentive plans to motivate their employees generally earn higher returns on equity than their counterparts over four years. Based on these studies, it can be concluded that companies with strong performance rewards practices achieve better long-term financial performance than companies with lower performance rewards practices (Delery & Doty, 1996). In addition, Huselid (1995) further concluded that there is a link between HR practices and organizational outcomes. Instead of evaluating one HR practice (e.g., selective hiring), researchers assessed the simultaneous use of multiple HR practices and revealed that HR practices were significantly related to productivity, financial performance and workforce retention (Huselid, 1995).

Other the other hand, several studies provided a rather mixed result. For example, Godard (2004) investigated the effect of HR practices (i.e., high-performance work practices) on the employer, labour and the workforce union.

The results of the analysis showed that HR practices did not have a positive impact on unions and workers compared to traditional HR activities, but offered some marginal benefits to companies. Similarly, Rodriguez and Ventura (2003) found that the adoption of compensation practices actually reduced organizational productivity. Subsequently, however, the results showed that other HR practices, such as job security and extensive training experience, have a positive impact on employee turnover and overall organizational performance.

Based on the above review and evidence of the universalistic theory, it is suggested that the “best-practice” approach is a valid SHRM concept (Delery & Doty, 1996) that does not yield synergies among HR practices, but rather views them as an additive (Lertxundi & Landeta, 2011). It has also been demonstrated that the benefits generated from HR practices might vary from organization to organization (Godard, 2004; Wood & Menezes,1998).

3.3. The Contingency Theory

While there are some scholars who strongly believe that the universalistic theory is the best way to help companies achieve better performance. Some scholars might have a different opinion and believe that the contingency theory is the better alternative for a company to maximize its performance because it considers HR practices to be constant with the company’s overall business strategies.

More specifically, the contingency theory, also known as the “best-fit” approach which is defined as a management technique in which the effectiveness of management is contingent, or dependent, and varies depending on the situations and environment (Agarwal,1982; Delery & Doty, 1996). In other words, the “best-fit” approach suggests that there is no ‘one best way’ to manage an organization’s workforce, and therefore, organizations should adopt a set of practices that ‘fit’ with the organization’s choice of strategy (Gilmore & Williams, 2013). Researchers also argued that it is unreasonable to simply apply the “best practice” approach to the entire company, as certain parts of a company may have more growth opportunities and require more special attention than others (Schuler & Jackson, 1987). Organizations that utilize HR practices that are appropriate for their strategies will achieve better performance. For instance, Sung and Ashton (2005) identified that there are over 30 HR practices that could contribute to organizational success, ranging from sophisticated recruitment, performance appraisals, self-direct teams, rewards system and so on. One of the downsides of the universalistic theory is that it ignores potentially significant differences between sectors, organizational sizes and countries. Because not all combinations of HR practices enable organizations to gain the same competitive advantage, a set of practices might work with one organization and not necessarily for another. It is sensible to believe that a small Japanese architecture company would have different HR criteria than a multinational medicine company located in the United States (Gilmore & Williams, 2013).

Under different circumstances, organizations should therefore determine and formulate the best approach that will 'fit' with the organization.

Furthermore, researchers also proposed that the contingency theory should be reinforced with the stage of the business life cycle (Redman & Wilkinson 2009). It is believed that the needs of a business in its start-up phase require different HR practices than those in its growth, maturity and decline phases. (Baird & Meshoulam, 1998). In other words, the effectiveness of HR practices would be different depending on the stage of organizational development. As organizations evolve and develop, HR practices need to be reformulated to meet new objectives. In addition, in line with the growth and development models, it is suggested that HRM will become more complex through a series of stages as organizations become more diverse (Baird & Meshoulam, 1998). Researchers also emphasized that HR practices should be targeted to encourage certain behaviours that are consistent with the company's business strategy. Therefore, organizations should not only utilize different HR practices for the purpose of business growth but should also consider using different HR practices to facilitate individual needs. (Delery & Doty, 1996).

3.4. The Contingency Theory and Business Life Cycle

Several studies on the relationship between HRM and a company's business life cycle also illustrated that business development influences HR practices. For recruitment policy, Leung (2003) proposed that during the initial stage of a business, the primary focus would be on market survival. Therefore, it is critical for organizations to recruit people that are ambitious and willing to explore uncertainty. As the organizations grow beyond the start-up stage, the objective might also transfer from market survival to a more systematic and professionalized entity development. HR managers should therefore recruit candidates with much more diverse skill-sets to support future business growth. Similarly, Baird and Meshoulam (1988) also proposed that the use of HR practices depends on the life cycle of an organization. During the start-up phase, HRM activities tend to be casual and informal and are likely to be carried out by the founder. Activities tend to focus on HR issues related to hiring and evaluating employee performance. Whereas during the growing phase, HR managers are hired, formal HR practices are put in place, and the focus is on employee compensation, training, and development. In the maturity phase, organizations are likely to be focused on performance assessment, employee relationships and a wider range of other HR issues (Baird and Meshoulam, 1988). Finally, in an economic downturn, organizations are likely to be forced to lay off employees or shift to other activities. Rapid organizational learning becomes critical. Therefore, managers must ensure that all employees receive appropriate training and guidance, depending on the situation (Nijssen & Paauwe, 2012).

3.5. Miles and Snow's organizational strategies

Another way to look at the contingency theory is to link HR activities with organizational strategy (Miles & Snow, 1978). The basic principle of this matching process is that when management attributes and capabilities are consistent with the organizational strategy, then a better business performance will result (Guest, 1997; Torrington et al., 2005; Wilkinson et al., 2016). According to Miles and Snow (1978), there are mainly four types of organizational strategies, being Prospector, Defender, Analyser and Reactor, which are listed in table 1.

Table 1: Miles & Snow's (1978) Organizational strategies model

Miles & Snow's Organizational	
Prospector	Analyser
Defender	Reactor

Prospector- If organizations belong to this category, they would always be at the forefront of innovation and development. Rather than waiting for opportunities to come, these companies tend to inspire others and take advantage of new ideas that assist them in achieving their objective of becoming the market leader. Based on this idea, researchers suggested that organizations would typically invest heavily in people who have the ability to drive and create potential opportunities.

Defender- When organizations fall into the defender category, they often operate in a mature and stable environment with relatively low complexity and dynamics.

For this reason, organizations tend to aggressively seek to prevent the entry of competitors. Defenders also pay less attention to other developments and threats outside their environment, rather they are looking for different ways to increase revenue through market penetration. Based on this situation, researchers suggested that organizations would typically have centralized control and a vertical information sharing system.

Analyser- The third type of organizational strategy is called the analyser. It is a unique combination of the prospector and defender. If organizations belong to this category, they would have the ability to minimize risk while increasing profitability. This strategy is difficult to pursue and tends to be adopted by large corporations, as these organizations have the capability to develop new ideas as well as maintain the market position that they have already created. Based on this situation, researchers suggested that organizations would typically require managers to handle various developments, controls and reward systems simultaneously.

Reactor- When organizations fall into the category of the reactor, they are typically the ones that can only react to the situation when the problem occurs. This adaptive way of work usually results in poor performance. Researchers also suggested that these organizations do not follow any pattern or systematic approaches, instead of handle each situation differently each time.

Once the company has identified its own organizational strategies, managers must therefore design and structure practices that could fit within the company's overall strategy. For instance, a prospector company might want to introduce more instruments to enhance collaboration and information sharing, as prospectors tend to drive creativity and new ideas in their sector. Whereas HR managers that are working in the defender type of companies could introduce training programmes to improve operational efficiency. It is also important to point out that it would be difficult for an organization to maintain a single strategy. Because an organization that was once considered an ‘innovator’ will progressively become a ‘defender’ due to fewer-innovation possible. (e.g., food process industry) (Miles & Snow, 1978).

3.6. Schuler and Jackson’s organizational strategies

Similar to the above organizational strategy provided by Miles and Snow (1978). Schuler and Jackson (1987) also suggested that the contingency theory should be linked with the business strategy, namely cost reduction, innovation and quality enhancement. Table 2 provides examples of how business strategies may require different approaches to managing day-to-day operations, and hence a better performance can be achieved with the help of HR-related software.

Table 2: Schuler & Jackson's (1987) - strategic orientations

Cost reduction	Innovation	Quality-enhancement
• Relatively repetitive and predictable behaviours	• High degree of creative behaviour	• Relatively repetitive and predictable behaviours
• A rather short-term focus	• A longer-term focus	• A more long-term or intermediate focus
• Primarily autonomous or individual activity	• A relatively high level of cooperation and interdependent behaviour	• A modest amount of cooperative, interdependent behaviour
• Modest concern for quality	• A moderate degree of concern for quantity	• A high concern for quality
• High concern for the quantity of output	• An equal degree of concern for process and results	• A modest concern for the quantity of output
• Primary concern for results	• A greater degree of risk-taking	• High concern for the process (how the goods or services are made or delivered)
• Low risk-taking activity	• A high tolerance of ambiguity and unpredictability	• Low risk-taking activity
•A relatively high degree of comfort with stability		• Commitment to the goals of the organization

For example, if an organization is implementing an innovation strategy (e.g., Apple, Dyson and Tesla). HR managers should offer a wider range of training programs that encourage employees to discuss problems via collaboration, and allow greater autonomy. Whereas, if the organization is focusing on a cost-leadership strategy (e.g., Ryanair, Lidl and Primark). It would be sensible for managers to tailor a specific training program for a particular task to ensure that there is little room for ambiguity (Schuler & Jackson, 1987). If possible, managers should also closely monitor salary levels to ensure that organizational expenses are at a minimum.

Besides, Arthur (1994) believed that the implementation of HR practices could be influenced by the competitiveness of the organization. For example, an organization focused on a cost leadership strategy might seek to minimize direct labour costs or improve procedures through designated policies and HR practices. In contrast, in an organization that strives for quality and innovation, HR managers should adopt HR practices that might influence employee attitudes by creating a psychological connection between the organization and its employees. Jackson et al. (1989) even suggested that it may be better for organizations that want to foster innovation to offer fewer incentives and focus on job security and training. In other words, HR practices should focus on developing trustworthy and committed employees who understand that failure is part of innovation (Arthur, 1994).

3.7. Evidence of the Contingency Theory

Batt and Moynihan (2004) studied different types of call centres in the United States. The data were based on responses from 350 managers in the telecommunications industry. The results of the analysis showed that managers who practiced a higher level of engagement had twice the retention rate of managers who practiced a lower level of engagement. This pattern was also reflected in sales growth: managers who practiced a higher level of engagement experienced more than twice the sales growth compared to their peers. This view was also supported by Arthur (1994), who examined performance differences using an empirical taxonomy. The findings also indicated that organizations that pursue product and quality differentiation and emphasize collaboration, training and higher pay tend to have lower scrap rates, employee turnover and higher productivity than those that adopt cost leadership strategies.

Besides, Youndt et al. (1996) examined the two HPWS views, namely the "best-practice" approach and the "best-fit" approach with almost 100 manufacturing plants located in the United States. The results of the analysis suggested that the alignment of HR practices is directly related to several dimensions of organizational performance. However, the subsequent analysis also revealed that this primary impact was the result of linking HR practices to a high-quality manufacturing strategy (i.e., "best-fit" approach).

Based on the results of over 360 companies, Guests et al. (2003) came to a mixed conclusion. Researchers suggested that higher retention rates and profit per employee are associated with greater use of HR practices. However, taking into account the profitability of previous years, these associations cease to be significant (Guest et al., 2003). In other words, researchers concluded that there is a positive relationship between HR practices and organizational performance, but could not confirm that the presence of HR practices can lead to changes in firm profitability. Moreover, some researchers further proposed that the relationship between HPWS and employee performance may not be a straightforward linear relationship. Some practices may even contradict each other and cause confusion. (Ogbonna & Whipp, 1999; Wilkinson et al., 2016).

For instance, it would be difficult for an organization to utilize a “pay for individual performance” practice while emphasizing teamwork and collaboration.

In addition, Cappelli and Neumark (2001); Godard (2004); Way (2002) were unable to find any performance gains from HPWS, and White et al. (2003) also concluded that there is no association between employee’s well-being and HPWS. Ogbonna and Whipp (1999) further argued that many of the researchers assume that the “best-fit” model can be targeted and measured. However, in reality, most organizations may have to switch practices depending on the environment, and any practices that “fit” previously might need to change.

Overall, the contingency theory approach suggests that organizations should adopt a set of practices that ‘fit’ with the organization’s choice of strategy (Gilmore & Williams, 2013). For example, HR managers should adopt HR practices that are related to their business stage (Leung, 2003) or the overall aim of the business (Miles & Snow,1978; Schuler & Jackson,1987). An organization focused on a cost leadership strategy might seek to minimize direct labour costs or improve procedures through designated policies and HR practices. In contrast, in an organization that strives for quality and innovation, HR managers should adopt practices that might influence employee attitudes by creating a psychological connection between the organization and its employees.

3.8. The Configurational Theory

The third concept of HPWS is the configurational theory. This approach is very similar to the contingency theory, which proposes that the alignment of HR practices with organizational strategy is an important factor. However, unlike the contingency theory, the configurational theory considers the pattern of HR practices as a critical element in achieving organizational performance (Browning et al., 2009). It creates multiple, reinforcing conditions that enhance workforce motivation, given that each individual has the required skills and capability to perform tasks effectively (Ichniowski et al., 1997; MacDuffie, 1995). Moreover, the configurational theory to SHRM "not only stresses the need for practices that are contingent with organisational circumstances, but in addition emphasizes the need for horizontal or internal fit" (Sparrow et al., 2004, p.158).

According to Delery and Doty (1996, p.804), the configuration theory can be referred to as "a concept that examines how the pattern of multiple independent variables is related to a dependent variable rather than with how individual independent variables are related to the dependent variable". It is based on the assumption that different types of HR practices will require vertical integration and horizontal integration (i.e., the pattern of HR practices) (Delery & Doty, 1996). Vertical integration refers to HR practices that must fit with the organizational goals, whereas horizontal integration refers to all HR practices and activities that must fit together to enhance business performance.

From the perspective of the configuration theory, the core idea is that the impact of HR practices on organizational performance depends on the effectiveness of the combination of HR practices, often referred to as HR practice “bundles” (MacDuffie, 1995). In other words, HR practices do not have that much impact on performance when implemented individually, but when all practices are bundled together, they can yield great productivity and performance (Ichniowski et al., 1997; MacDuffie, 1995). Dyer and Reeves (1995, p.657) also suggested that “the logic in favour of bundling (practice) is straightforward. Since employee performance is a function of both ability and motivation, it makes sense to have practices aimed at enhancing both”. For example, in order to effectively carry out ‘selective hiring’, companies must also have a comprehensive rewards system and training program in place to enhance overall HR practices. Or, simply allowing employees to work in a self-managed team does not guarantee business success, it must also incorporate performance evaluations to ensure the objectives are met.

Researchers further suggested that what matters the most is that organizations must combine all practices into a coherent bundle to create a better work environment in order to maintain employee satisfaction and gain competitive advantage (Armstrong, 2006; Cardon & Stevens, 2004; Sharma, 2009; Sung & Ashton, 2005; Terpstra & Rozell, 1993). In addition, it is worth mentioning that the configurational theory proposes that there are multiple, equally effective ways that can go hand-in-hand with delivering the same desired outcome (Wilkinson & Johnstone, 2016).

3.9. Evidence of the Configurational Theory

Configurational theorists have sought to investigate the relationship between HR practices and business performance. For example, Delery and Doty (1996) compare practices within two configurational systems, namely market-based and in-house systems. The results of the analysis indicated that there is some positive relationship between the staffing bundles and firm performance, particularly in terms of return on assets (ROA) and return on equity (ROE). The positive link between HR practices and business performance appearing in most of the models were contingent compensation, extensive training, careful selection and involvement. MacDuffie (1995, p.201) also suggested that in his research, the workforce will only exercise discretionary behaviours when they “believe that their individual interests are aligned with those of the company and that the company will make a reciprocal investment in their well-being”. The findings of the analysis indicated that flexible manufacturers with team-based systems, reduction of status barriers between management and employees, and investment in workforce training consistently outperform traditional mass production manufacturers. Researcher also concluded that variables capturing two-way and three-way interactions among the bundles of HR practices are even better predictors of performance (MacDuffie, 1995).

Besides, Ketchen et al. (1997) carried out a meta-analysis by aggregating 40 configurations-performance studies. Researchers suggested that the configurational theory does enhance performance and in particular for organizations that have broad sets of organizational dimensions. Results of the analysis also revealed that those studies which were focusing on a single industry had also experienced a greater imparts effect. However, researchers did not find any support that a specific combination of practices would enhance greater business performance (Delaney & Huselid, 1996).

In addition, serval studies provided rather mixed results, Gooderham et al. (2008) examined the relationship between HR practices and organizational performances from over 3,200 companies located in Europe. The results indicated that five of the six bundles 'control practices' such as assessing performance towards the individual or at the team level have a significant impact on performance, and two of the three bundles 'intermediary practices' such as career development and downsizing methods also have a significant impact on performance. However, none of the six bundles of 'commitment-based practices' has any impact on organizational performance. The results further proposed that the overall effect of HR practices on performance is relatively modest (Gooderham et al., 2008). Similarly, when Stavrou and Brewster, (2005) evaluated the possible bundles of HR practices over 3700 companies within the EU. Their results suggested that only seven bundles are significantly related to performance, six of which have a positive and one of which has a negative relationship with performance (Stavrou & Brewster, 2005).

Based on the above review of configuration approaches, it has been suggested that there are multiple equally effective bundles of practices that can work in tandem to achieve the same desired outcome (Wilkinson & Johnstone, 2016). Therefore, organizations should tailor HR practices based on the concepts of vertical and horizontal integration (Delery & Doty, 1996), where vertical integration refers to the need for HR practices to align with organizational goals, and horizontal integration refers to the fact that all HR practices and activities must work together to improve business performance.

4.0. Study Two Hypotheses

Technological advancement is associated with the impact of globalisation and the emergence of the new knowledge economy. Therefore, it would be interesting to examine the links between SHRM and HR analytics. At an organizational level, SHRM is viewed as the most important element that directly influences organizational performance (Geet et al., 2009) while technology development such as HR analytics is changing the way how an organization operates (Eubanks, 2019). To address the research gap about: *What factors influence the use of HR analytics from a company perspective? Specifically, how does the complexity of HR systems and variable pay systems influence the use of HR analytics?* This thesis will be proposing three hypotheses with six control variables as written below.

4.1. Variable pay systems

Besides structural factors of firms, managerial practices such as the type of monetary rewards and variable pay would influence the incidence of HR analytics. More specifically, we believe that managers are more willing to use HR analytics when a company's variable pay is based on individual performance. It is because HR analytics provide additional information that helps managers improve the accuracy of performance appraisals, and perceptions of fairness among employees may also be greater. Several studies have shown that HR practices such as individual variable pay systems have a positive impact on employee performance (Cable & Judge, 1994; Cadsby et al., 2007; Trank et al., 2002) and employee retention (Harrison et al., 1996; Nyberg, 2010; Salamin & Hom, 2005; Shaw, Dineen, Fang, & Vellella, 2009). For example, in a study presented by Lazear (2000), the researcher concluded that workforce productivity increases by 44% when a company shifts from fixed salaries to individual variable pay. In addition, HR practices such as HR analytics are believed to be of greater benefit when the number of variable pay systems in an organization becomes more complex (e.g., when the number of employees increases or when employee performance and teamwork are evaluated) (Batt, 1999; Hauff et al., 2014; Gooderham et al., 2015; Parry, 2011). Therefore, it would be reasonable to assume that HR analytics would be a useful tool to ensure that an appropriate performance appraisal plan is in place for organizations using an individual variable pay system when compared to other variable pay systems, such as a team performance pay system and a corporate performance pay system.

Furthermore, one of the main goals of any organization is to improve its performance and achieve a sustainable competitive advantage. In the context of SHRM, one of the examples that organizations can use to enhance the performance of their employees is the variable compensation system. The idea behind this is to motivate employees and recognize their efforts through rewards (i.e., variable compensation) (Stone et al., 2020), which in turn leads to better employee performance. With the increasing technological development in HR, managers are now able to effectively measure the performance of their employees through HR analytics.

Hypothesis:

H1: The incidence of HR analytics would be higher when variable pays is measured based on individual performance since HR analytics enable managers to generate accurate information to provide incentives.

4.2. Firm process

Another management practice worth mentioning is the idea of complex processes in organizations (e.g., the number of variable compensation systems, training needs assessment, hierarchical structures within organizations, the number of managers and complex coordination between (groups of) employees and teamwork). When an organization has several or more of these complex processes, HR practices such as HR analytics are thought to be of greater benefit (Batt, 1999; Hauff et al., 2014; Gooderham et al., 2015; Parry, 2011). Studies such as Maduenyi et al. (2015) and Nahm et al. (2003) also found that organizational effectiveness and its relationship with various structural dimensions (i.e., number of hierarchical levels, degree of horizontal integration, locus of decision making, type of formalization, and level of communication) are also correlated, with results indicating that number of hierarchical levels, degree of horizontal integration, and type of formalization have direct, significant, and positive effects on locus of decision making.

In addition, companies operating in different environments require different combinations of practices and processes to sustain the day-to-day operations of the organization. Relying on a fixed set of practices without considering the ever-changing business environment (e.g., political, economic and legal) is likely to put companies at risk. Similarly, for SHRM, organizations need to incorporate HR practices to effectively manage their workforce. Therefore, when HR practices and processes become too complex, managers would be more needed to use HR-related technologies such as HR analytics to manage their workforce.

Hypothesis:

H2a: The incidence of HR analytics is higher when a firm has more complex firm processes as HR analytics would be more needed to provide information and suggestion to managers.

H2b: The more the company uses monetary rewards in managing employees, the more it needs to use HR-related technologies to generate accurate information, which reflects the rate of HR analytics adoption.

4.3. Firm size

The firm size (C1) is one of the control variables. We believe that organizational factors play an important role in evaluating the use of HR analytics. In particular, the structural characteristics of firms, (e.g., size, operating culture, and ownership), as well as managerial characteristics and complexity of firm processes (e.g., the role and form of reward practices, hierarchies, teamwork, and managerial responsibilities) also influence the frequency of HR analytics. For example, the number of employees in a company would be one of the factors influencing the use of different HR practices (Florkowski & Olivas-Luján, 2006; Hausdorf & Duncan, 2004). Therefore, it would be reasonable to assume that the size of a company also matters for the use of HR analytics. Larger companies may be more inclined to adopt HR analytics because larger companies tend to have a more standardized process to collect and analyse data, benefit from greater bargaining power and economies of scale (Hirsche, 2016), while smaller companies may be largely personal in the sense that HR managers are aware of all employee matters (e.g., performance level and work attitude).

Eder and Igbaria (2001) examined the relationships between company size and intranet diffusion in a cross-sectional survey. The results revealed that the earliness of adoption, top management support and company size are positively associated with the adoption of technological innovations. Similarly, Giunta and Trivieri (2007) and Moch and Morse (1977) examined the causal relationship between the adoption of new information technologies and firm size and suggested that the adoption of information technologies is positively related to firm size because as firm size increases, “economies of scale” are created that make it easier to adopt and benefit from new technologies.

Besides, in a study conducted by Thong (1999), the researcher examined more than 165 companies in Singapore and concluded that of the three organizational characteristics assessed, company size, information intensity, and workforce knowledge of information systems were the most important organizational characteristics. The most important organizational characteristic determining the level of information systems adoption was company size, and the researchers found out that the result confirmed that smaller companies tend to adopt fewer information systems than larger companies because of their needs and the availability of resources.

4.4. Firm age

Another factor worth mentioning is the idea of firm age (C2), (i.e., years since its establishment). Researchers suggested that the “age” of firms is one of the determinants that why and how certain HR practices are used to win an organization (Benders et al., 2006; DiMaggio & Powell, 1983; Scott, 2001). In general, it appears that the longer a company has been in business, the less likely it is to adopt new HR practices and tools. This is because older companies have a long history and strong traditions have already been embedded in organizational structures and practices (Kok et al., 2003; Wager, 1998), resulting in a higher resistance rate to new HRM practices compared to newly established companies. Management might also consider new HR practices that would affect and compromise the current structure and responsibilities of the organization.

For example, Haller and Siedschlag (2008) used survey data from Irish manufacturing companies to indicate that company age has a positive influence on the introduction and use of the Internet and electronic sales. However, in a study conducted by Ben-Youssef et al. (2010), researchers did not find a difference when they examined the relationship between firm age and information and communication technology (ICT) adoption. Similarly, Khalifa (2016) evaluated the diffusion rate of CT in Tunisia using data from a sample of 145 companies. The results showed that company size, affiliation to a multi-unit company, and strategic decisions were important variables in predicting the adoption of CT. However, the analysis showed that firm age, competition, and sector activity were not related to CT adoption (Khalifa, 2016). Other studies such as Bayo-Moriones and Lera-Lopez (2007), Bertschek and Fryges (2002), Bocquet and Brossard (2007), and Choi et al. (2011) also showed no significant correlation between firm age and ICT adoption.

4.5. Business ownership

It is not surprising that when there is a structural change in ownership, the entire business operation, including HRM practices, is affected. (Croonen et al., 2016). Specifically, a change in ownership (C3) creates new opportunities for strategic realignment and restructuring of the firm, which can facilitate new ideas (Thompson and Wright, 1995) such as utilising HR analytics for making decisions. The idea of value creation through a change in ownership would tend to be greater for a firm operating in less developed industries. Managers operating in these industries tend to have more autonomy in business development and incremental innovations that are not possible under the previous ownership regime (Wright et al., 2000; Wright et al., 2001). There is also evidence that when ownership changes, management not only provides more training to its employees but also provides a better incentive plan for its employees (Bruining et al., 2005; EVCA, 2001; Wright et al., 1992). In addition, a new owner may have a new business strategy that requires a change in human resource policies. The uncertainty associated with the change in ownership may require additional investment in human resources to build trust between employees and the new owner (Bruining et al., 2005). Therefore, it can be assumed that a change in ownership and management increases the likelihood that new HR practices such as HR analytics will be implemented in the absence of a change in ownership.

4.6. Employee-management relationship

The question of whether or not the relationship status between managers and employees matters for the incidence of HR analytics (C4). Evidence suggests that a good relationship between management and employees facilitates the adoption of HR practices, as employees trust that the new practices introduced by management will be mutually beneficial (e.g., Bissola & Imperatori, 2014; Parry & Strohmeier, 2014; Parry & Tyson, 2011).

4.7. Market competitiveness

In order to convince organizations to change their existing HR practices for HR analytics, they must believe it is necessary. For example, market competitiveness (C5) (i.e., market pressure) could be considered one of the ways to encourage management to use HR analytics in their operations (Levenson, 2018). Market competitiveness refers to the total number of suppliers or retailers competing in the same market to provide similar goods and services to consumers (Hansen & Mowen, 2014). Thus, if a company feels that it has an incentive to implement HR analytics to manage its workforce in a way that gives it a competitive advantage to outcompete other competitors, it is more likely that the company would implement HR analytics. There are perfect competition, Monopolistic competition, Oligopoly and Monopoly.

4.7.1. Perfect competition

Perfect competition is one of the market structures with a large number of firms. A market with perfect competition has the following four characteristics in particular:

(1) Equilibrium state: there are many suppliers in the industry, and the sales volume of each supplier accounts for only a small part of the total sales volume. There is no single supplier who can influence the price of the product or service. The price of the product is determined according to the supply and demand in the market (Brent, 2004).

(2) Product homogeneity: the products or services produced by each supplier in the market are homogeneous and do not differ from each other. Besides, consumers only pay attention to the price, and there is no subjective preference for individual suppliers (Brent, 2004).

(3) No barriers to entry and exit: all suppliers are free to enter and exit the market whenever possible (Forssbaeck & Oxelheim, 2014).

(4) Complete market information: Each supplier and customer has completed all the essential market information and is assumed to make rational decisions to maximize their self-interest (Brent, 2004).

4.7.2. Monopolistic competition

Monopolistic competition can be defined as the exact opposite of perfect competition, where the product and service are not homogeneous and there are few barriers to entry and exit (Gans et al., 2003). However, similar to perfect competition, monopolistic competition also have a large number of suppliers and consumers in the market, and no firm has complete control over the market price. In other words, a monopolistic competition is when there are many suppliers that produce products that are different from other but serve for the same purpose (McEachern, 2016). The products of these companies are interchangeable but differ from each other (e.g., in terms of brand and quality).

4.7.3. Oligopoly

An oligopoly is a form of market competition in which there are barriers to entry (e.g., economies of scale, patents, expensive and complex equipment), which means that only a few firms can operate in the market (Dransfield, 2013). Typically, there are a small number of large firms that supply products to a large number of consumers. Because there are only a few suppliers, various forms of collusion can occur in an oligopoly market, affecting competition in the market and ultimately leading to higher prices and a decline in quality (Dransfield, 2013; Free & Free, 2010).

4.7.4. Monopoly

Last but not least, a monopoly is a competitive market where only one supplier offers a product or service for which there are no close substitutes (Boone et al., 2019). The supplier can easily adjust its price and decide how much it is willing to offer consumers. It is generally believed that the main reason for a monopoly is barriers to entry (e.g., exclusive legal privileges, control of sources of supply, or patented products). Table 3 provides an overview of the different types of market competitiveness in different factors, such as number of suppliers, product type, information transparency and barrier of entry.

Table 3: A summary of market competitive type

Market competitive type	Perfect competition	Monopolistic competition	Oligopoly competition	Monopoly competition
Number of Supplier	A lot of suppliers in this market	More suppliers than in the oligopoly market but less than in the perfect market	Not a lot of suppliers in this market, between two to twenty suppliers	Only one operate in this market
Product type	Identical product or service	There is difference in product quality or price	More or less the same, but might have some differences in product quality or price	Exclusive, unique and not be substituted
Information transparency	Fully transparent	Transparent but not as good as perfect competitive	Only few information but usually within the market	No information at all
Barrier of entry	Extremely easy, no	Easy	Difficult	Extremely difficult, high

	barrier			barriers to entry
Real example	Agricultural and foreign exchange markets	Hotel, restaurant and consumer service business	Car, airplane manufacturing and soft drink markets	Microsoft, Apple IOS and households water supplier markets

In addition, DiMaggio and Powell (1983) suggested that there are three key mechanisms behind the institutional isomorphic change, namely coercive isomorphism (CI), mimetic isomorphism (MI), and normative isomorphism (NI). CI refers to the similarity of one organization's structure to that of another, whether as a result of imitation or independent development under similar constraints. That is, if an organization feels pressure from its competitors who are using HR analytics, it is likely to follow. MI describes the extent to which organizations imitate the organizational structure of competitors because they believe the competitor's structure is advantageous. Last but not least, NI refers to pressure from professionals with similar educational backgrounds who tend to approach problems in similar ways. In fact, this behaviour indirectly pushes the norm to the organization that encourages others to adopt HR analytics.

4.8. Legal and political factors

From an institutional perspective, elements such as legal and policy elements may also play an important role in explaining differences in the use of HRM practices across countries (C6) (e.g., DeFidelto & Slater, 2001; Goergen et al., 2013). Different countries may have different regulations and policies in place to protect the analysis and sharing of employee data, which explains differences in the prevalence of HR analytics in different countries. For example, many Central and Eastern European Countries (CEECs), including the United Kingdom, have a liberal approach, meaning that managers often have more prerogatives in the use of HR practices. This ideology of strictness in data protection and privacy regulations across countries is largely consistent with the classification of capitalist varieties (VoCs) developed by Hall and Soskice in 2001 (Hall & Soskice 2001).

Furthermore, researchers suggested that the idea of VoC also plays a role with respect to data privacy, data collection and storage regulations (Rothstein et al., 2019). For instance, countries such as the Netherlands, Germany and Belgium would be under the category of coordinated market economies (CMEs) where stricter data protection regulations apply. Liberal market economies (LMEs) such as the United Kingdom, Ireland, and Malta, on the other hand, take a more relaxed approach to data privacy, collection, and retention.

In a study conducted by Ellmer and Reichel (2021), researchers also suggested that HR analytics practitioners in Germany had to justify their 'need-to-knows' and the 'business needs' for which they utilized specific data in their analyses. In other words, in order to comply with the data protection law, HR analytics users would only have limited access to data, which severely hampers HR analytics practitioners' ability to conduct and develop analytics outputs.

4.9. Dependent variable

For the dependent variable, question 23 has been selected. Specifically, it asked: “Does this establishment use data analytics to monitor employee performance?” and, participants would be able to answer either “Yes” or “No” for this question. In here, data analytics could be referred to as descriptive analytics, predictive analytics and prescriptive analytics.

4.9.1. Independent variables

In order to evaluate how different types of variable pay (H1) influence the use of HR analytics. We used answers to the question “How many employees at this establishment received the following types of variable pay?”, (1) Payment by results, for example, piece rates, provisions, brokerages or commissions. (2) Variable extra pay linked to individual performance following management appraisal. (3) Variable extra pay linked to the performance of the team, working group or department. (4) Variable extra pay linked to the results of the company or establishment (profit-sharing scheme). And, each question follows answer categories into 7 groups, being “None at all”, “Less than 20%”, “20% to 39%”, “40% to 59%”, “60% to 79%”, “80% to 99%” and “All”.

With regard to the complexity of firm processes and management for (H2a), we selected five questions that are expressed in a different dimension of firm complexity. First, we included question 25 about: “How many hierarchical levels do you have in this establishment?” and participants would be able to indicate the number of hierarchical levels within their organization. The second question refers to teamwork where we selected question 17: “With regard to the employees doing teamwork, do most of them work in a single team or do most of them work in more than one team?” and participants would be able to answer either “No teams”, “Most of them work in a single team” and “Most of them work in more than one team” Furthermore, we used question 34: “How many employees in this establishment are in jobs that require continuous training?”, and participants would be able to select one of the following: “None at all”, “Less than 20%”, “20% to 39%”, “40% to 59%”, “60% to 79%”, “80% to 99%” and “All”. The forth question, we used question 13: “How many people that work in this establishment are managers?”, and participants would be able to select one of the following: “None at all”, “Less than 20%”, “20% to 39%”, “40% to 59%”, “60% to 79%”, “80% to 99%” and “All”. Last but not least, we have also included the total number of variable pay systems an organization use as an independent variable to test out whether there are any differences in the incidence of HR analytics or not. In addition, to evaluate how the frequency of monetary rewards (H2b) influence the use of HR analytics, we used the answers to the question “How often are the following practices used to motivate and retain employees at this establishment?” which were “Very often”, “Fairly often”, “Not very often” and “Never”.

4.9.2. Control variables

Regarding the control variables, for (C1), how company size influences the use (i.e., incidence*)* of HR analytics, we used answers to the question "Approximately how many people work in this establishment?" which were grouped into 5 categories, being 10-19 employees; 20-49 employees; 50-249 employees; 250-499 employees and more than 500 employees. For (C2) about the age of the firms, we calculated the year of operation using the answers to the question "Since what year has this establishment been carrying out this activity?".

Furthermore, with regard to how business ownership might influence the incidence of HR analytics in organizations (C3). We used the answer to the question "Since the beginning of 2016, has there been any change in the ownership of the company to which this establishment belongs?" and participants would be able to answer from one of the three following: "Yes, and it involved a change of management", "Yes, but management remained the same" or "No".

With regards to the "relationship" between the managers and employees (C4), we used answers to the question "How would you describe the relations between management and employees in this establishment in general?" by differentiating between "Very good", "Good", "Neither good nor bad", and "Bad or very bad".

In terms of (C5), we examined the incidence of HR analytics based on the competitiveness of the market that a firm is operated in, we used answers, "Not at all competitive”, “Not very competitive”, “Fairly competitive”, and “Very competitive” to the question 66 “How competitive would you say the market for the main products or services provided by this establishment is?” In addition, we also included the company business industry when analysing the incidence of HR analytics to understand how each sector react differently when implementing HR practices (Laursen, 2002; Strohmeier & Kabst, 2009).

As regards to the role of institutional (C6), juridico-political factors express the ability of firms to make use of HR analytics. We used the VoC classification developed by Hall and Soskice (2001). Given that there is a continuous debate with respect to which EU countries should be considered as CME or LME or something else. For the test of (C6), it was primarily comparing the classical CME countries by referring to Hall and Soskice (2001) and European Commission (2008). Therefore, we have put Austria, Belgium, Denmark, Finland, Germany, Slovenia, Luxembourg, Netherlands and Sweden in the category of CME. Bulgaria, Croatia, Estonia, Hungary, Latvia, Lithuania, Romania, Slovakia, Slovenia, UK, Ireland, Czech Republic (Czechia), Malta, and Cyprus are in the category of LME while Greece, Spain, France, Italy, and Portugal are under SME (European Commission, 2008).

5.0. Method

The purpose of this section is to explain and discuss the methodology used. It begins with an introduction about the nature of the data and then moves on to discuss the logic of why the logistic regression model was adopted for research questions two. Besides, it also introduces the dependent, independent, and control variables before presenting the research findings.

5.1. Nature of the thesis data

The data in this paper comes from the 2019 European Company Survey (ECS), which focuses on a different aspect of company operations (e.g., Houten & Russo, 2020) and covers 28 European countries and more than 20,000 company cases, including HR practices, skills utilization, skills strategies, digitalization, direct employee involvement, and social dialogue. The goal of the ECS is to help practitioners identify "bundles of workplace practices" that lead to outcomes that benefit both employees and employers.

5.2. Target population

The target population was all companies with ten or more employees in economic sectors operating in the market throughout Europe. Industries such as agriculture, forestry and fishing mining (A), quarrying (B), manufacturing (C), electricity, gas, steam and air conditioning supply (D), water supply, sewerage, waste management and remediation activities (E), construction (F), wholesale and retail trade, repair of motor vehicles and motorcycles (G), transportation and storage (H), accommodation and food service activities (I), information and communication (J), financial and insurance activities (K), real estate activities (L), professional, scientific and technical activities (M), administrative and support service activities (N), public administration and defence; compulsory social security (O), education (P), and human health and social work activities (Q) arts, entertainment and recreation (R) and other service activities (S), activities of the household (T) and activities of extraterritorial organizations and bodies (U) were all included in the ECS 2019.

Besides, the survey was conducted online and had to be tailored for different types of respondents, such as managers in a company with one or more plants or employee representatives acting as individuals or as part of a council or delegation. The characteristics of the respondents were also taken into account when formulating the questions. For example, for organizations that had been operating for less than three years at the time of the survey, any questions about events in the past three years were phrased to apply to the entire period of the organization's operation. This survey was adopted in this thesis because the ECS has the advantage that it includes a question on the use of HR analytics which is not commonly included in other datasets, most notably the CRANET dataset, which is frequently used in the field of international and comparative HRM. Specifically, the ECS data is representative for businesses and organizations with 10 or more employees throughout the EU and thus enables us to test our hypotheses on a large sample of countries with different institutional and market contexts.

5.3. Logistic regression model

Because the dependent variable is dichotomous and it should reflect the predicted probabilities at “ 0 ” and “ 1 ”. If the company is marked as “ 0 ”, it means the company is not using HR analytics to monitor employee performance whereas if the company is marked as “ 1 ”, it means the company is using HR analytics to monitor employee performance. Therefore, the author decided to use a logit specification in the analysis. To test the hypotheses, it estimates the influence of each independent variable, adjusted for other variables. Furthermore, due to the ECS response being gathered from 28 EU countries, it cannot assume that the errors can be distributed independently. Since the dependent variable is a dichotomy, the effect should reflect the predicted probability (bounded by 0 and 1). Therefore, it appreciates a multi-level (logit) model that contains country-specific random sections, the estimate a *multilevel logistic model* which includes a country-specific random intercept that follows the form of:

$$\ln\left(\frac{p}{1-p}\right) = \gamma_{00} + \gamma_{10}X1_{ij} \ldots + \gamma_{k0}Xk_{ij} + \gamma_{01}W1_{j} \ldots + \gamma_{0k}Wk_{j} + u0_{j}$$

Where p is the probability that companies use HR analytics; γ_{00} is the conditional grand mean; $\gamma_{10}, \ldots, \gamma_{k0}$ is the set of coefficients that consider firm-level variables $X1_{ij}, \ldots, Xk_{ij}$; while $\gamma_{01}, \ldots, \gamma_{0k}$ is the set of coefficients that consider a wider range of variables, for example at a macro-level $W1_{j}, \ldots, Wk_{j}$. The coefficients can be evaluated as linear effects on the “log-odds” of using HR analytics. $u0_{j}$

represents the country-specific error for which the variance σ_{u0}^2 is estimated, and is assumed to be zero-mean normally distributed. The firm-level variance is implied by the binomial distribution. Moreover, based on the data set provided by the ECS, we noticed that ECS uses a stratified sample based on company size and industry, creating unequal probabilities of sample inclusion according to the value of these variables. We solve this problem by including sector and size as covariates in all estimated models to ensure that the errors are conditionally independent.

5.4. Standard error

The standard error provides information about the quality of the estimated parameter". The more individual values there are, the smaller the standard error, and the more accurate the unknown parameter can be estimated. It is important to note that every statistic has a standard error associated with it (Gravetter & Larry, 2016; Perry, 1995). A standard error of " 0 " means that the statistic has no random error. The representation of the population data, with the sample is closely distributed around the population. Meanwhile, the higher the number of standard errors, the less accurate the statistic and does not accurately represent the population data. In other words, the smaller the standard error, the more representative the sample will be of the overall population (Gravetter & Larry, 2016; Perry, 1995).

5.5. Log-likelihood

The log-likelihood value of a regression model is a measure of the model fit. The higher the log-likelihood value, the better the model fits the data set (i.e., the closer the negative value to zero) (Pampel, 2020). For example, a higher log likelihood value for one model (-90.00) than another model (-120.00) should indicate that the first model is a better fit to the data. In addition, the log likelihood value for a particular model can range from negative infinity to positive infinity (Pampel, 2020). It is important to note that log-likelihood values cannot be interpreted as fit indices alone, as they are a function of sample size (Halli et al., 1992; Ward & Ahlquist, 2018). Therefore, the likelihood values should be compared with the likelihood values of another model.

5.6. Ontology and epistemology

Before deciding which methodology to adopt for the thesis, it is important to be clear about the philosophical basis of the research idea. Specifically, these background assumptions inform the methods of data collection, analysis and interpretation of the thesis (Cordeiro et al., 2015). Both ontology (i.e., what is there for people to know, the reality and existence of things) and epistemology (i.e., how is knowledge created and what is possible to know) are two concepts that come from the philosophical perspective. They are based on the idea of how philosophers see the world, and in what form of belief is most appropriate for a particular context.

Ontology is about the idea of the nature of reality (Rawnsley, 1998; Urmson & Ree, 1989). Perhaps the most important question ontology addresses is whether the social phenomena we study should be understood as existing objectively (i.e., realism, objectivism) (Bryman & Bell, 2015; Cameron & Price, 2009). Or, is the element of object that can be manipulated by the activities of people (i.e., constructionism) (Bryman & Bell, 2015; Bell, et al., 2018; Cameron & Price, 2009). While epistemology is referred to how an individual understands knowledge, how they understand their own thinking process in a situation, and what does it mean to say that someone knows (Greene et al., 2016). In other words, epistemology addresses the question "How can I know reality?" (Audi, 2011; Keegan 2009). Moreover, within epistemology, there are also two different branches that are mostly relevant with business studies. Firstly, the belief that knowledge can be measured using reliable designs and tools as an outsider (i.e., positivism) (Brown, 2022). Secondly, the belief that reality needs to be interpreted to discover the underlying meaning (i.e., interpretivism) (Brown, 2022). And, when the thesis combines both the ontology and epistemology together, then the philosophers/ researchers would be able to get a holistic view of how to generate and understand knowledge (i.e., research paradigm).

Moreover, it is important point out that historically, social sciences research including HRM mainly relied on either qualitative or quantitative approaches (Leung; 2021; Pierce 2008). The differences between quantitative approach and qualitative approach were usually view as completely the opposite side of a spectrum. The quantitative approach followed the positivist paradigm, the objective here is to discover how organization’s policy and regulation (e.g., HR practices) shape employees’ behaviour. In other words, this research philosophy approach is frequently linked with scientific studies that are primarily data driven and follow statistical analysis (Lastrucci, 1963). While, the qualitative approach followed the interpretivist paradigm, in which the objective here is to find out how employees shape and interact with the organization from personal experience. The idea is that each individual are intricate and complex, different people might experience and view the same regulation (e.g., HR practices) differently.

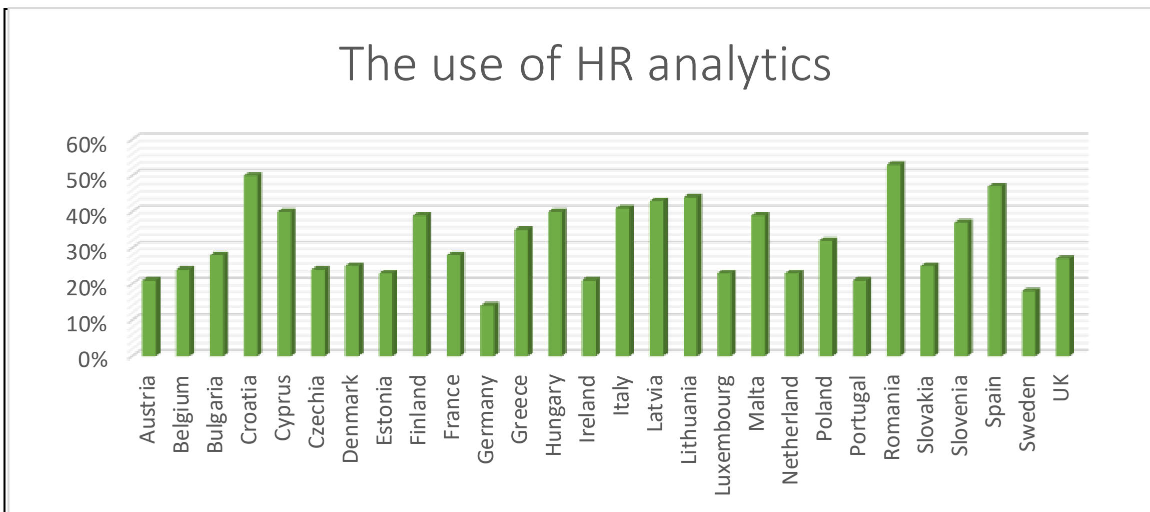
5.7. Methodological Framework

Despite the differences between the positivist and interpretivist viewpoints. A positivist paradigm (i.e., qualitative method) will be used to answer the above research question. Considerations such as the objectivity of the survey and the large quantity of data set from the Eurofound led to the judgement that a qualitative method would yield more meaningful results. In the framework of the quantitative methods, a multilevel logistic model and will be used with the European Company Survey (ECS) data. For this study, the dependent variable is dichotomous and represented whether the company used HR analytics to monitor employee performance or not. It will be taken from the ECS to test out a list hypothesis with control variables that have presented in the previous section.

8.0. Results - Study Two

The benefit of HR analytics has successfully spurred discussion among practitioners and scholars. However, the results of the thesis suggest that there are only about 32% of firms using HR analytics to monitor employee performance. Of the 21869 sample companies, only 20047 companies answered this question with 6499 (32%) companies use HR analytics and 13548 (68%) companies do not.

Moreover, the results did not find any major differences across different juridico-political zones. This is illustrated in Graph 1, which shows the percentage of firms that make use of HR analytics across all 28 EU countries. Here, the results suggest that the incidence of HR analytics, for instance, is relatively high in Romania (53%), Croatia (50%), and Spain (47%), but lower in Germany (14%), Sweden (18%), Denmark (25%) and Finland (39%). An overall pattern is that firms in Nordic countries and coordinated market economies, in general, seem less inclined to use HR analytics than their counterparts in the central and eastern parts of Europe.



Graph 1

In terms of industry sectors, the results suggest that HR analytics use is, for instance, relatively high in finance (38%), manufacturing (37%) and mining &

quarrying (35%), but lower in real estate (17%), art, entertainment & recreation (16%) and construction (22%).

With reference to the results of the research analysis (see appendix), we present the estimates for five multilevel logit models where the significant levels are presented by the number of stars (e.g., *p<0.05, ** p<0.01, ***p<0.001). The significance level is the probability of rejecting the null hypothesis when it is true. For example, a significance level of 0.01 indicates a 1% risk of concluding that a difference exists when there is no actual difference. The full set of rewards and payment systems variables are included in all five models with the coefficients of the company size, sector and age being the dummies. However, the five models vary in the inclusion of different macro and micro-level variables.

Model 1 is the simplest model out of the 5 models, containing the different variables mentioned in the previous sections (i.e., frequency of monetary rewards, variable pay systems, company size, sector and age). Model 2 includes three additional control variables, namely “change in ownership”, “teamwork” and “market competitiveness”. Model 3 builds on the previous model and adds the “country factors” variable and “company hierarchical level” control variable. Model 4 includes all the previous variables but also take into account the “relationship with manager” control variable and model 5 includes all the previous macro and micro control variables with two extra control variables, being the “continuous training needs” control variable and the “manager percentage” control variable.

Table 4: A summary hypotheses table

Study Two			
Dependent Variable: The use of HR analytics	Accept	Decline	Partially
H1: The incidence of HR analytics would be higher when variable pays is measured based on individual performance since HR analytics enable managers to generate accurate information to provide incentives.			✖
H2a: The incidence of HR analytics is higher when a firm has more complex firm processes as HR analytics would be more needed to provide information and suggestion to managers.	✖		
H2b: The more the company uses monetary rewards in managing employees, the more it needs to use HR-related technologies to generate accurate information, which reflects the rate of HR analytics adoption.	✖		

Regarding the type of variable pay (H1) (see Table 4, Table 5 and Table 6), the results reveal that it is highly significant for companies using the results-based pay method and HR analytics. One of the reasons for this is that companies that offer results-based pay can easily be flexible, making it easier to tailor the analysis of data about their employees. In other words, HR analytics is more likely to be adopted in organizations that rely on “pay by result” because these organizations have a strong incentive to measure and track employee performance. Performance-based pay systems are designed to reward employees who meet or exceed certain performance targets, so organizations that use these systems need accurate data on employee performance in order to make informed pay decisions. Therefore, HR analytics provides a way for managers to measure employee performance in real-time, and to identify areas for improvement, which is critical for organizations to drive business results. Surprisingly, however, the results for “pay linked to individual performance” are not robust enough to conclude that there is a strong significant correlation between the variables. Of the five models, models 1, 2, 3, and 4 show some level of significance between “pay linked to individual performance” and the use of HR analytics. A number of factors can influence this relationship, including the complexity of the organization, the nature of the work performed, and the availability of resources to invest in analytics. Additionally, organizational culture, leadership style, and the extent to which employees are empowered to make decisions and drive change can also play a role. In other words, the incentive to adopt HR analytics may be influenced by reasons other than just about the variable pay system.

Regarding the complexity dimension (H2a), The overall results show that the number of hierarchy levels has an influence on the use of HR analytics. Hierarchy levels 2, 3, 4 and 5 are all significant. The higher the hierarchy level, the higher the coefficient. This can be seen by the fact that the coefficient for level 2 is 0.396, for level 3 is 0.630, for level 4 is 0.845, and for level 5 is 0.836, with a p-value is < 0.001. The complexity of an organization can impacts the adoption and effective use of analytics. This is due to several factors, including data availability and business processes. Complex organizations often have a large amount of data that needs to be analyzed, making it difficult to manage and understand without the help of analytics tools. Analytics can provide a comprehensive view of an organization's performance by bringing together all data sources. In addition, complex organizations often have multiple departments with their own data and metrics, as well as complex business processes. Analytics can help provide the data and insights needed to make effective decisions and drive business performance. However, this pattern does not seem to hold when companies have more than five levels of hierarchy. We assume that the number of companies with six or seven levels is rather small, so the statistical estimate is less precise. When employees work in more than one team, there is a higher use of HR analytics. As the coefficient shows, it is positively significant at 0.541 and the p-value is < 0.001 compared to employees who do not work in a team (model 3). Regarding employee training, the results also support the hypothesis that training complexity is positively associated with the use of HR analytics. Not only does this pattern seem to hold for all levels, but it also seems to become stronger for each additional level where the coefficient is 0.301 for Model 1, 0.329 for Model 2, 0.518 for Model 3, 0.632 for Model 4, and 0.809 for Model 5 ($p < 0.001$). The results suggest reinforces the idea that HR analytics is more embedded in organizations and departments that require complex training routines. Besides, we found no correlation between the number of managers and the use of HR analytics. Again, it should be noted that the number of observations for “40% to 59%,” “60% to 79%,” and “80% to 100%” is relatively small, so these estimates should be carefully examined. Regarding the complexity of the influence of variable pay systems on the use of HR analytics, the results suggest that companies that use more than a single variable pay system are more likely to incorporate HR analytics into their HR practices. This pattern seems to hold not only for all five models, but also becomes stronger for each additional system. For example, for model 3: This is shown by the fact that the coefficient for companies using two variable pay systems is 0.140 with a p-value is < 0.05, for using three variable pay systems 0.310, for using four variable pay systems 0.413 with a p-value is < 0.001.

One of the reasons why the number of variable pay systems can impact the use of HR analytics is due to the need for integration. Complex organizations often have a variety of pay systems and processes in place, including payroll, benefits, talent management, and others. In order to get a complete and accurate view of performance data, it is necessary to integrate data from these different systems and processes. HR analytics can help to streamline data integration and provide a single source of truth for workforce's performance data, which can improve the accuracy and usefulness of HR insights and drive better decision making. Additionally, by integrating data from multiple HR systems and processes, organizations can gain a more comprehensive view of the employee lifecycle, which can inform talent management strategies and improve overall HR performance.

In addition, the frequency of use of monetary rewards (H2b) is positively associated with the use of HR analytics because organizations that rely on performance pay are more likely to have a focus on measuring and tracking employee performance. In order to effectively implement and manage a performance pay system, organizations need to have access to accurate and relevant data on employee performance. HR analytics can provide this data, which can inform decisions around pay, bonuses, promotions, and other performance-based rewards.

Overall, the positive association between the frequency of use of monetary rewards and the use of HR analytics reflects the importance of accurate and relevant data in supporting effective performance management and decision making in organizations that rely on performance pay. For example, model 3 shows that companies that use monetary rewards “very often” have a coefficient value of 0.571, “fairly often” have a coefficient value of 0.403 with a p-value is < 0.001. And, companies that use monetary rewards “not very often” have a coefficient value of 0.208 with a p-value is < 0.01 compared to companies that never use HR analytics.

Table 5: Statistical results summary - (Research question two)

	Model 1			Model 2			Model 3			Model 4			Model 5		
	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p
Statistical results summary															
Research question two															
Rewards practices: monetary rewards															
Never (Ref)															
Very often	0.675***	0.086	0.001	0.580***	0.087	0.001	0.571***	0.087	0.001	0.561***	0.088	0.001	0.538***	0.089	0.001
Fairly often	0.496***	0.070	0.001	0.426***	0.071	0.001	0.403***	0.071	0.001	0.399***	0.072	0.001	0.385***	0.073	0.001
Not very often	0.281***	0.067	0.001	0.235***	0.068	0.001	0.208**	0.068	0.010	0.206**	0.068	0.010	0.197**	0.069	0.010
Type of variable pay systems															
Pay by results	0.031**	0.011	0.010	0.031**	0.011	0.01	0.031**	0.011	0.010	0.031**	0.011	0.010	0.027*	0.011	0.05
Pay by individual performance	0.022*	0.011	0.050	0.024*	0.011	0.05	0.022*	0.011	0.050	0.022*	0.011	0.050	0.021	0.011	> 0.050
Pay by team performance	0.009	0.012	> 0.050	0.003	0.012	> 0.050	0.004	0.012	> 0.050	0.003	0.012	> 0.050	-0.000	0.012	> 0.050
Pay by company performance	-0.006	0.009	> 0.050	-0.006	0.009	> 0.050	-0.006	0.009	> 0.050	-0.006	0.009	> 0.050	-0.009	0.009	> 0.050
Number of pay system a company use															
None at all (Ref)															
Single pay system	0.091	0.092	> 0.050	0.078	0.093	> 0.050	0.079	0.093	> 0.050	0.079	0.093	> 0.050	0.061	0.094	> 0.050

Two pay systems	0.162**	0.061	0.010	0.145*	0.061	0.05	0.140*	0.061	0.050	0.142*	0.062	0.050	0.141*	0.062	0.050
Three pay systems	0.365***	0.056	0.001	0.326***	0.056	0.001	0.310***	0.056	0.001	0.313***	0.057	0.001	0.308***	0.057	0.001
Four pay systems	0.468***	0.061	0.001	0.417***	0.061	0.001	0.413***	0.061	0.001	0.417***	0.061	0.001	0.403***	0.062	0.001
Team work															
No team (Ref)															
Single team				0.464***	0.0446	0.001	0.427***	0.0449	0.001	0.421***	0.0450	0.001	0.397***	0.0455	0.001
More than a team				0.579***	0.0495	0.001	0.541***	0.0497	0.001	0.537***	0.0498	0.001	0.496***	0.0504	0.001
Complexity of hierarchical levels															
No hierarchical levels (Ref)															
Two hierarchical levels							0.396***	0.113	0.001	0.392***	0.114	0.001	0.384***	0.115	0.001
Three hierarchical levels							0.630***	0.107	0.001	0.627***	0.107	0.001	0.614***	0.109	0.001
Four hierarchical levels							0.845***	0.113	0.001	0.840***	0.113	0.001	0.816***	0.115	0.001
Five hierarchical levels							0.836***	0.143	0.001	0.822***	0.143	0.001	0.788***	0.145	0.001
Six hierarchical levels							0.305	0.222	> 0.050	0.302	0.222	> 0.050	0.281	0.224	> 0.050
Number of managers															
None at all (Ref)															
less than 20%													0.178	0.092	> 0.050
20% to 39%													0.061	0.105	> 0.050
40% to 59%													-0.089	0.219	> 0.050
60% to 79%													-0.377	0.332	> 0.050
80% or more													-0.049	0.331	> 0.050
Require continuous training															
None at all (Ref)															
less than 20%													0.301***	0.064	0.001
20% to 39%													0.329***	0.069	0.001
40% to 59%													0.518***	0.076	0.001
60% to 79%													0.632***	0.080	0.001
80% or more													0.809***	0.072	0.001

Table 6: A summary results table

Hyp	Supported?	Finding
H1	Yes*	Companies that are using "individual performance-based pay method" are more likely to use of HR analytics to monitor employees performance
H2a	Yes***	The incidence of HR analytics is higher when a firm has more complex firm processes as HR analytics would be more needed to provide information and suggestion to managers.
H2b	Yes***	The results revealed that the more the company uses monetary rewards in managing employees, the more it needs to use HR-related technologies to generate accurate information, which reflects the rate of HR analytics adoption.

9.0 Study Two Conclusion

In summary, the goal of these two chapters (i.e., chapter 3 and 4) is to contribute to the SHRM literature by shedding light on how HPWS impacts an organization's business performance. Specifically, it explored how HR analytics can improve the idea of HR functions, which is a long-term goal of an organization that can be achieved with the help of new technologies. Theory such as the universalistic theory (i.e., "best-practice" approach), the contingency theory (i.e., "best-fit" approach), and the configurational theory were also included to present different opinions and views on this topic. In addition, Miles and Snow's (1978) and Schuler and Jackson's (1987) organizational principles were also discussed, with the researchers emphasizing that HR practices should be linked to the overall strategy of the organization.

Overall, this chapter has successfully provided information and a theoretical foundation on how HR analytics as an HR practice can improve organizations. Specifically, it highlights how HR analytics can be used to increase productivity and organizational performance and improve managerial decision making. In each of the sections, the rationale is clearly laid out and illustrated with relevant examples of how HR analytics enables HR managers to discover useful information and hidden relationships in organizations.

Chapter 4: Study Three - Does HR analytics have an impact on a company's performance?

1.0. Introduction

According to Marler and Boudreau (2017), Mittal and Gujral (2020), Oracle (2019), and Tambe et al. (2019), there is an ongoing discussion about the strategic role of analytics in the HRM industry. As technology continues to advance, organizations are expected to streamline HR processes, reduce administrative burdens, improve services, provide real-time metrics that enable decision makers to identify trends. However, above all, technology such as HR analytics makes HR a more strategic role in the organization (Johnson & Gueutal, 2011), that is, the long-term goals of the organization can be achieved by measuring and understanding employee behaviour with unprecedented accuracy

(Dahlbom et al., 2019). This perspective which reflects perfectly with the idea of Strategic Human Resource Management (SHRM), particularly with regard to the High-Performance Work System (HPWS) and each of the perspectives, such as the universalistic theory (i.e., best-practice), the contingency theory (i.e., best-fit) and the configurational theory.

Therefore, the structure of the chapter will first focus on the idea of SHRM, HPWS as well as the universalistic theory, the contingency theory and the configurational theory. Then, the research question, hypotheses, methodology, results, discussion, and conclusion will be presented. It is important to note that this study covers both the qualitative and quantitative (i.e., two parts; main effect analysis & interaction effect analysis) aspects, which provides a more comprehensive picture of how HR analytics affects a firm's financial performance and how HR analytics can be optimally implemented if a firm decides to do so.

The purpose of this study is to answer the question of how HR analytics actually has an impact on a firm's performance, as well as on whether or not HR analytics might influence the relationship between employee motivation level, variable pay systems influence and a firm’s financial performance.

2.0. Overview of Strategic Human Resource Management

Given the growing importance of human resources in organizations, SHRM has never been more important than now (Armstrong & Baron, 2002; Boxall, 1996;

Hendry & Pettigrew 1986; Paauwe & Boon, 2018; Wright et al., 2005). In order to gain maximum effect from HRM, SHRM theory emphasizes the need for HRM strategies and HR practices to be developed within the context of overall business strategies and objectives (Nankervis et al., 2011). It is based on the assumption that SHRM considers the ‘macro’ perspective of the business (e.g., strategies and policies) and HR practices focus on the ‘micro’ perspective of the business (e.g., activities, functions and processes), which relates to how managers handle HRM functions such as hiring, performance evaluation, reward, employment relationship, and development in the light of business strategy (Nankervis et al., 2011). SHRM goes beyond the functional concept of HRM by considering other elements such as matching resources to the present and future objectives of organizations, employment relationships, and structure and culture changes (Agarwal, 2008). In general, SHRM is concerned with employee problems and practices that are related to or affected by the organization’s strategic plan. The main objectives of SHRM are: (I) to provide all of the necessary elements to motivate employees in the organization to achieve sustainable competitive advantage. (II) To ensure both the organization and the needs of employees are met by developing and implementing HR practices (e.g., HR analytics) that are consistent with the business strategy (Agarwal, 2008; Strohmeier, 2009).

In order to fully understand how HR analytics might influence SHRM, it is important to define and understand the idea of SHRM. One of the best-known definitions was proposed by Wright and McMahan (1992, p.298), who described

SHRM as “the pattern of planned human resource deployments and activities intended to enable an organization to achieve its goals.” While, Bagga and Srivastava (2014, p.2) refer to SHRM as the “linking of human resources (HR) with organizations’ strategic goals and objectives so as to improve business performance and develop organizational culture that nurtures innovation, flexibility and competitive advantage. linking of human resources (HR) with organizations’ strategic goals and objectives so as to improve business performance and develop organizational culture that nurture innovation, flexibility and competitive advantage”. Hendry and Pettigrew (1986) suggested that there are four components that make the SHRM ecosystem, which include:

5. The use of planning in human resource management
6. An integrated approach to the design and implementation of HR systems
7. Matching HRM policies and activities with the business strategy of the company
8. Viewing people as a strategic resource for the achievement of “competitive advantage”

In addition, Armstrong and Brown (2019, p.8-9) made it clear that SHRM is “the overall approach that provides guidance on how key issues of human resource management can be dealt with strategically so as to best support the achievement of corporate goals”.

3.0. HPWS and evidence

The concept of HPWS is a human resource approach that gained substantial academic attention in the mid-1990s (Pfeffer, 1998; Wilkinson et al., 2014). In some cases, this approach may also be referred to as the 'best-practice HRM' approach (Marchington and Wilkinson, 2002), the 'high-involvement HRM' approach (Wilkinson et al., 2016) or the 'high-commitment HRM' approach (Gould-Williams, 2004). In fact, the main concept behind all of the terminologies is defined as "a set, or bundle, of human resource management practices related to selection, training, performance management, compensation, and information sharing that are designed to attract, retain, and motivate employees" (Messersmith & Guthrie, 2010, p.242). Therefore, results in greater individual and organizational performance (Appelbaum et al., 2000; Becker et al., 1998; Delery & Doty, 1996; MacDuffie, 1995). By following the concept of HPWS, employees are more likely to be committed to the organization, enjoy greater autonomy to develop relevant skills, and assist organizations in achieving higher productivity (Appelbaum et al., 2000; Guthrie, 2001; Tomer, 2007). HPWS views employees as the reason for organizations' competitive advantage, rather than as a typical source of expense. (More information in Chapter 3, page 80-82).

Besides, one of the most compelling pieces of evidence regarding the link between SHRM implementation and organizational performance is provided by Professor John Purcell and his colleagues at the University of Bath for the CIPD.

(Armstrong & Brown, 2019). In their longitudinal research, Professor Purcell and his colleagues concluded that there is a positive relationship between positive attitudes to HR policies, practices, levels of satisfaction, motivation, commitment and operational performance (Armstrong & Brown, 2019). Similarly, Huselid and Becker (1997) examined over 700 firms with regard to the impact of the presence of HPWS and its effectiveness and alignment with firms' competitive strategy on the shareholder. The results of the analysis support the assumption that HPWS has an economically positive and significant impact on business performance.

A study conducted by Kling (1995) revealed that when organizations introduced formal training programs to their employees, organizations typically experience a 19% increase in productivity compared to their counterparts. Moreover, researchers also revealed that there is a roughly 20% decrease in time in manufacturing products when organizations implement gainsharing practices. Similarly, Appelbaum et al. (2000) interviewed nearly 4,400 workers in more than 40 manufacturing facilities to evaluate the impact on HPWS (e.g., plant performance). The results of the study showed that through collaboration and training, workers greatly accelerated their manufacturing process and were able to meet consumer demand for faster delivery time.

Macky and Boxall (2007) used national employee survey data to examine how the process of using HPWS practices would foster employee emotion and engagement. Researchers found that the commitment created by HPWS is causally flowing through the mediating effects of employee-level job satisfaction and trust in management (Macky & Boxall 2007). Moreover, a study published by Garcia-Chas et al. (2014) examined the perceptions of more than 150 employees from 19 different companies on HPWS and various mediating variables. Researchers found that HPWS is positively related to job satisfaction, procedural justice, and intrinsic motivation. However, only job satisfaction mediated the relationship between HPWS and retention, while intrinsic motivation and procedural justice mediated the relationship between job satisfaction and HPWS.

Besides, Veth et al. (2019) used data from more than 1,500 employee surveys to examine (I) the relationship between perceived availability and use of HRM practices and employee outcomes (i.e., job engagement and employability), and (II) how employee age moderates these relationships. The results suggested that HRM practices related to learning, development, and incorporation of new tasks may be positively associated with work engagement and employability. However, the results also revealed that age does not change or experience a significant moderating effect on the relationship between HRM and employee performance. (Veth et al., 2019).

Furthermore, Khatri (2000) used over 190 largest companies in all major industries in Singapore to examine the relationship between ‘HR practices and business strategy’ as well as ‘HR practices and company performance’. The results of the study revealed that overall business strategy directly affects HR practices, which in turn affects firm performance. Thus, business strategy has a moderating effect on the relationship between HR practices and organizational performance (Khatri, 2000).

Other studies also have illustrated that there is a positive correlation between HPWS and business performance (Guthrie, 2001; Wright et al., 2005). For instance, productivity with business performance (Ichniowski et al., 1997) and employee retention levels with business performance (Arthur, 1994; Huselid, 1995). Besides, Combs et al. (2006) conducted a meta-analysis of more than 90 contemporary research studies on the basis of the HPWS-performance relationship. The results also indicated that when the standard deviation of the use of HPWS increases by one, it leads to a 4.6% increase in return on resources, and a 4.4% decrease in turnover (Paracha et al., 2014).

Although it might be reasonable to assume that HRM practices and organizational performance are correlated according to various studies. (Appelbaum et al., 2000; Armstrong et al., 2010; Bae & Lawler, 2000; Batt, 2002; Birdi et al., 2008; Collins & Smith, 2006; Collings et al., 2010; Combs et al., 2006; Datta et al., 2005; Delaney & Huselid, 1996; Delery & Doty, 1996; Guthrie, 2001; Huselid, 1995; Kim & Wright, 2011; Lee et al., 2012; MacDuffie, 1995; Purcell et al., 2003; Sun et al., 2007; Youndt et al., 1996; Way, 2002). However, some studies do also show that there is a contradiction when looking at the concept of HPWS (Malizia et al., 2017; Ogbonnaya et al., 2016). Kroon et al. (2009) argued that HPWS does not provide the same mutual benefits to workers and employers (i.e., mutual benefit - employees enjoy greater job flexibility and better compensation plans, and employers benefit from higher productivity and greater employee retention). Researchers suggested that the additional productivity and business performance achieved through HPWS is the result of requiring employees to work harder and handle heavier workloads (Kroon et al., 2009). Similarly, this view is supported by Godard (2001), who studied more than 500 employees in Canadian companies that have implemented HPWS, and found that high-performance practices are strongly associated with intrinsic rewards, but also cause higher levels of stress and anxiety among employees.

In addition, researchers have suggested that the relationship between HPWS and performance is influenced by the "black box" of HR practices, particularly within the methodology (Fleetwood & Hesketh, 2010; Paauwe, 2009; Purcell et al., 2003). While it is possible to make empirical observations when utilizing HR practices (input phase) and measuring company performance (output phase), it can be difficult to determine through research what is happening between these two phases. (i.e., would the company have produced the same results if it had adopted the same HR practices?)

The sections above focused on concepts related to SHRM and HPWS. Specifically, it provided an overview of HPWS and explored how HPWS can potentially create a competitive advantage for organizations, as well as the concerns associated with HPWS. The following paragraphs will explore the "best-practice" approach (universalistic theory), the "best-fit" approach (contingency theory) and the configurational theory, and their relationship with HR functions.

3.1. The Universalistic Theory

Universalistic is “the simplest form of theoretical statement in the SHRM literature because they imply that the relationship between a given independent variable and a dependent variable is universal across the population of organizations” (Delery & Doty, 1996, p.805). The link between company performance and the “best-practice” is well documented in HRM theory (Gilmore & Williams, 2013; Kaufman & Miller, 2011; Sirmon & Hitt, 2009; Vlachos, 2009). There is a long list of HR practices that can be combined to influence company performance (Armstrong, 2006; Kintana et al., 2006; Vlachos, 2009). There is a perception that there is ‘one best way’ to manage employees in order to improve business performance. It is worth noting that the idea of the universalistic theory (i.e., best-practice approach) does not yield any synergy effects between the HR practices, but rather considers that they are additive (Lertxundi & Landeta, 2011). It is therefore based on the assumption that the more HR practices are implemented, the better results a company can achieve. The hypothesis proposes that HR practices would impact linearly on organizational performance, such as employee knowledge, productivity and economic success.

In addition, it is important to remember that there is no agreement on a single set of HR practices that can guarantee to achieve the same level of performance (Wilkinson et al., 2016). For instance, Terpstra and Rozell, (1993) proposed that there are five recruitment practices that could be adopted to improve organizational performance (Terpstra & Rozell, 1993). In contrast, Pfeffer (1998) suggested that there are exactly seven practices that guarantee an organization to gain a competitive advantage regardless of the environment or industry in which the firm operates (Redman & Wilkinson, 2002; Malik, 2018; Price 2007). Moreover, one manager may select one practice while others may not. For instance, Huselid (1995) believed that 'variable pay' practice is the core focus of HPWS but Arthur (1994) believes otherwise. Despite the differences in identifying all of the desired indicators. The "best-practice" would generally include, careful selection, training, mentoring, incentives, knowledge-sharing and other shared decision-making mechanisms.

3.2. Evidence of the Universalistic Theory

In general, many researchers would agree that the use of "best-practice" can enhance business performance (Delery & Doty, 1996). For example, Terpstra and Rozell (1993) proposed that certain recruitment practices, such as structured interviews, validation and cognitive tests are positively related to a firm's profitability. Similarly, Gerhart and Milkovich (1990) found that companies that included contingent pay systems in their HR practices (i.e., rewards and compensation policy) performed better financially. Leonard (1990) has also shown that companies that use long-term incentive plans to motivate their employees generally earn higher returns on equity than their counterparts over four years. Based on these studies, it can be concluded that companies with strong performance rewards practices achieve better long-term financial performance than companies with lower performance rewards practices (Delery & Doty, 1996). In addition, Huselid (1995) further concluded that there is a link between HR practices and organizational outcomes. Instead of evaluating one HR practice (e.g., selective hiring), researchers assessed the simultaneous use of multiple HR practices and revealed that HR practices were significantly related to productivity, financial performance and workforce retention (Huselid, 1995).

Other the other hand, several studies provided a rather mixed result. For example, Godard (2004) investigated the effect of HR practices (i.e., high-performance work practices) on the employer, labour and the workforce union. The results of the analysis showed that HR practices did not have a positive impact on unions and workers compared to traditional HR activities, but offered some marginal benefits to companies. Similarly, Rodriguez and Ventura (2003) found that the adoption of compensation practices actually reduced organizational productivity. Subsequently, however, the results showed that other HR practices, such as job security and extensive training experience, have a positive impact on employee turnover and overall organizational performance.

Based on the above review and evidence of the universalistic theory, it is suggested that the “best-practice” approach is a valid SHRM concept (Delery & Doty, 1996) that does not yield synergies among HR practices, but rather views them as an additive (Lertxundi & Landeta, 2011). It has also been demonstrated that the benefits generated from HR practices might vary from organization to organization (Godard, 2004; Wood & Menezes,1998).

3.3. The Contingency Theory

While there are some scholars who strongly believe that the universalistic theory is the best way to help companies achieve better performance. Some scholars might have a different opinion and believe that the contingency theory is the better alternative for a company to maximize its performance because it considers HR practices to be constant with the company's overall business strategies.

More specifically, the contingency theory, also known as the "best-fit" approach which is defined as a management technique in which the effectiveness of management is contingent, or dependent, and varies depending on the situations and environment (Agarwal,1982). In other words, the "best-fit" approach suggests that there is no 'one best way' to manage an organization's workforce, and therefore, organizations should adopt a set of practices that 'fit' with the organization's choice of strategy (Gilmore & Williams, 2013). Researchers also argued that it is unreasonable to simply apply the "best practice" approach to the entire company, as certain parts of a company may have more growth opportunities and require more special attention than others (Schuler & Jackson, 1987). Organizations that utilize HR practices that are appropriate for their strategies will achieve better performance. For instance, Sung and Ashton (2005) identified that there are over 30 HR practices that could contribute to organizational success, ranging from sophisticated recruitment, performance appraisals, self-direct teams, rewards system and so on. One of the downsides of the universalistic theory is that it ignores potentially significant differences between sectors, organizational sizes and countries. Because not all combinations of HR practices enable organizations to gain the same competitive advantage, a set of practices might work with one organization and not necessarily for another. It is sensible to believe that a small Japanese architecture company would have different HR criteria than a multinational medicine company located in the United States (Gilmore & Williams, 2013). Under different circumstances, organizations should therefore determine and formulate the best approach that will 'fit' with the organization.

Furthermore, researchers also proposed that the contingency theory should be reinforced with the stage of the business life cycle (Redman & Wilkinson 2009). It is believed that the needs of a business in its start-up phase require different HR practices than those in its growth, maturity and decline phases. (Baird & Meshoulam, 1998). In other words, the effectiveness of HR practices would be different depending on the stage of organizational development. As organizations evolve and develop, HR practices need to be reformulated to meet new objectives. In addition, in line with the growth and development models, it is suggested that HRM will become more complex through a series of stages as organizations become more diverse (Baird & Meshoulam, 1998). Researchers also emphasized that HR practices should be targeted to encourage certain behaviours that are consistent with the company's business strategy. Therefore, organizations should not only utilize different HR practices for the purpose of business growth but should also consider using different HR practices to facilitate individual needs. (Delery & Doty, 1996).

3.4. The Contingency Theory and Business Life Cycle

Several studies on the relationship between HRM and a company's business life cycle also illustrated that business development influences HR practices. For recruitment policy, Leung (2003) proposed that during the initial stage of a business, the primary focus would be on market survival. Therefore, it is critical for organizations to recruit people that are ambitious and willing to explore uncertainty. As the organizations grow beyond the start-up stage, the objective might also transfer from market survival to a more systematic and professionalized entity development. HR managers should therefore recruit candidates with much more diverse skill-sets to support future business growth. Similarly, Baird and Meshoulam (1988) also proposed that the use of HR practices depends on the life cycle of an organization. During the start-up phase, HRM activities tend to be casual and informal and are likely to be carried out by the founder. Activities tend to focus on HR issues related to hiring and evaluating employee performance. Whereas during the growing phase, HR managers are hired, formal HR practices are put in place, and the focus is on employee compensation, training, and development. In the maturity phase, organizations are likely to be focused on performance assessment, employee relationships and a wider range of other HR issues (Baird and Meshoulam, 1988). Finally, in an economic downturn, organizations are likely to be forced to lay off employees or shift to other activities. Rapid organizational learning becomes critical. Therefore, managers must ensure that all employees receive appropriate training and guidance, depending on the situation (Nijssen & Paauwe, 2012).

3.5. Miles and Snow's organizational strategies

Another way to look at the contingency theory is to link HR activities with organizational strategy (Miles & Snow, 1978). The basic principle of this matching process is that when management attributes and capabilities are consistent with the organizational strategy, then a better business performance will result (Guest, 1997; Torrington et al., 2005; Wilkinson et al., 2016). According to Miles and Snow (1978), there are mainly four types of organizational strategies, being Prospector, Defender, Analyser and Reactor, which are listed in table 1.

Table 1: Miles & Snow's (1978) Organizational strategies model

Miles & Snow's Organizational	
Prospector	Analyser
Defender	Reactor

Prospector- If organizations belong to this category, they would always be at the forefront of innovation and development. Rather than waiting for opportunities to come, these companies tend to inspire others and take advantage of new ideas that assist them in achieving their objective of becoming the market leader. Based on this idea, researchers suggested that organizations would typically invest heavily in people who have the ability to drive and create potential opportunities.

Defender- When organizations fall into the defender category, they often operate in a mature and stable environment with relatively low complexity and dynamics. For this reason, organizations tend to aggressively seek to prevent the entry of competitors. Defenders also pay less attention to other developments and threats outside their environment, rather they are looking for different ways to increase revenue through market penetration. Based on this situation, researchers suggested that organizations would typically have centralized control and a vertical information sharing system.

Analyser- The third type of organizational strategy is called the analyser. It is a unique combination of the prospector and defender. If organizations belong to this category, they would have the ability to minimize risk while increasing profitability. This strategy is difficult to pursue and tends to be adopted by large corporations, as these organizations have the capability to develop new ideas as well as maintain the market position that they have already created. Based on this situation, researchers suggested that organizations would typically require managers to handle various developments, controls and reward systems simultaneously.

Reactor- When organizations fall into the category of the reactor, they are typically the ones that can only react to the situation when the problem occurs. This adaptive way of work usually results in poor performance. Researchers also suggested that these organizations do not follow any pattern or systematic approaches, instead of handle each situation differently each time.

Once the company has identified its own organizational strategies, managers must therefore design and structure practices that could fit within the company's overall strategy. For instance, a prospector company might want to introduce more instruments to enhance collaboration and information sharing, as prospectors tend to drive creativity and new ideas in their sector. Whereas HR managers that are working in the defender type of companies could introduce training programmes to improve operational efficiency. It is also important to point out that it would be difficult for an organization to maintain a single strategy. Because an organization that was once considered an 'innovator' will progressively become a 'defender' due to fewer-innovation possible. (e.g., food process industry) (Miles & Snow, 1978).

3.6. Schuler and Jackson's organizational strategies

Similar to the above organizational strategy provided by Miles and Snow (1978). Schuler and Jackson (1987) also suggested that the contingency theory should be linked with the business strategy, namely cost reduction, innovation and quality enhancement. Table 2 provides examples of how business strategies may require different approaches to managing day-to-day operations, and hence a better performance can be achieved with the help of HR-related software.

Table 2: Schuler & Jackson's (1987) - strategic orientations

Cost reduction	Innovation	Quality-enhancement
• Relatively repetitive and predictable behaviours	• High degree of creative behaviour	• Relatively repetitive and predictable behaviours
• A rather short-term focus	• A longer-term focus	• A more long-term or intermediate focus
• Primarily autonomous or individual activity	• A relatively high level of cooperation and interdependent behaviour	• A modest amount of cooperative, interdependent behaviour
• Modest concern for quality	• A moderate degree of concern for quantity	• A high concern for quality
• High concern for the quantity of output	• An equal degree of concern for process and results	• A modest concern for the quantity of output
• Primary concern for results	• A greater degree of risk-taking	• High concern for the process (how the goods or services are made or delivered)
• Low risk-taking activity	• A high tolerance of ambiguity and unpredictability	• Low risk-taking activity
•A relatively high degree of comfort with stability		• Commitment to the goals of the organization

For example, if an organization is implementing an innovation strategy (e.g., Apple, Dyson and Tesla). HR managers should offer a wider range of training programs that encourage employees to discuss problems via collaboration, and allow greater autonomy. Whereas, if the organization is focusing on a cost-leadership strategy (e.g., Ryanair, Lidl and Primark). It would be sensible for managers to tailor a specific training program for a particular task to ensure that there is little room for ambiguity (Schuler & Jackson, 1987). If possible, managers should also closely monitor salary levels to ensure that organizational expenses are at a minimum.

Besides, Arthur (1994) believed that the implementation of HR practices could be influenced by the competitiveness of the organization. For example, an organization focused on a cost leadership strategy might seek to minimize direct labour costs or improve procedures through designated policies and HR practices. In contrast, in an organization that strives for quality and innovation, HR managers should adopt HR practices that might influence employee attitudes by creating a psychological connection between the organization and its employees. Jackson et al. (1989) even suggested that it may be better for organizations that want to foster innovation to offer fewer incentives and focus on job security and training. In other words, HR practices should focus on developing trustworthy and committed employees who understand that failure is part of innovation (Arthur, 1994).

3.7. Evidence of the Contingency Theory

Batt and Moynihan (2004) studied different types of call centres in the United States. The data were based on responses from 350 managers in the telecommunications industry. The results of the analysis showed that managers who practiced a higher level of engagement had twice the retention rate of managers who practiced a lower level of engagement. This pattern was also reflected in sales growth: managers who practiced a higher level of engagement experienced more than twice the sales growth compared to their peers. This view was also supported by Arthur (1994), who examined performance differences using an empirical taxonomy. The findings also indicated that organizations that pursue product and quality differentiation and emphasize collaboration, training and higher pay tend to have lower scrap rates, employee turnover and higher productivity than those that adopt cost leadership strategies.

Besides, Youndt et al. (1996) examined the two HPWS views, namely the “best-practice” approach and the “best-fit” approach with almost 100 manufacturing plants located in the United States. The results of the analysis suggested that the alignment of HR practices is directly related to several dimensions of organizational performance. However, the subsequent analysis also revealed that this primary impact was the result of linking HR practices to a high-quality manufacturing strategy (i.e., “best-fit” approach).

Based on the results of over 360 companies, Guests et al. (2003) came to a mixed conclusion. Researchers suggested that higher retention rates and profit per employee are associated with greater use of HR practices. However, taking into account the profitability of previous years, these associations cease to be significant (Guest et al., 2003). In other words, researchers concluded that there is a positive relationship between HR practices and organizational performance, but could not confirm that the presence of HR practices can lead to changes in firm profitability. Moreover, some researchers further proposed that the relationship between HPWS and employee performance may not be a straightforward linear relationship. Some practices may even contradict each other and cause confusion. (Ogbonna & Whipp, 1999; Wilkinson et al., 2016). For instance, it would be difficult for an organization to utilize a “pay for individual performance” practice while emphasizing teamwork and collaboration.

In addition, Cappelli and Neumark (2001); Godard (2004); Way (2002) were unable to find any performance gains from HPWS, and White et al. (2003) also concluded that there is no association between employee’s well-being and HPWS. Ogbonna and Whipp (1999) further argued that many of the researchers assume that the “best-fit” model can be targeted and measured. However, in reality, most organizations may have to switch practices depending on the environment, and any practices that “fit” previously might need to change.

Overall, the contingency theory approach suggests that organizations should adopt a set of practices that ‘fit’ with the organization’s choice of strategy (Gilmore & Williams, 2013). For example, HR managers should adopt HR practices that are related to their business stage (Leung, 2003) or the overall aim of the business (Miles & Snow,1978; Schuler & Jackson,1987). An organization focused on a cost leadership strategy might seek to minimize direct labour costs or improve procedures through designated policies and HR practices. In contrast, in an organization that strives for quality and innovation, HR managers should adopt practices that might influence employee attitudes by creating a psychological connection between the organization and its employees.

3.8. The Configurational Theory

The third concept of HPWS is the configurational theory. This approach is very similar to the contingency theory, which proposes that the alignment of HR practices with organizational strategy is an important factor. However, unlike the contingency theory, the configurational theory considers the pattern of HR practices as a critical element in achieving organizational performance (Browning et al., 2009). It creates multiple, reinforcing conditions that enhance workforce motivation, given that each individual has the required skills and capability to perform tasks effectively (Ichniowski et al., 1997; MacDuffie, 1995). Moreover, the configurational theory to SHRM "not only stresses the need for practices that are contingent with organisational circumstances, but in addition emphasizes the need for horizontal or internal fit" (Sparrow et al., 2004, p.158).

According to Delery and Doty (1996, p.804), the configuration theory can be referred to as "a concept that examines how the pattern of multiple independent variables is related to a dependent variable rather than with how individual independent variables are related to the dependent variable". It is based on the assumption that different types of HR practices will require vertical integration and horizontal integration (i.e., the pattern of HR practices) (Delery & Doty, 1996). Vertical integration refers to HR practices that must fit with the organizational goals, whereas horizontal integration refers to all HR practices and activities that must fit together to enhance business performance.

From the perspective of the configuration theory, the core idea is that the impact of HR practices on organizational performance depends on the effectiveness of the combination of HR practices, often referred to as HR practice “bundles” (MacDuffie, 1995). In other words, HR practices do not have that much impact on performance when implemented individually, but when all practices are bundled together, they can yield great productivity and performance (Ichniowski et al., 1997; MacDuffie, 1995). Dyer and Reeves (1995, p.657) also suggested that “the logic in favour of bundling (practice) is straightforward. Since employee performance is a function of both ability and motivation, it makes sense to have practices aimed at enhancing both”. For example, in order to effectively carry out ‘selective hiring’, companies must also have a comprehensive rewards system and training program in place to enhance overall HR practices. Or, simply allowing employees to work in a self-managed team does not guarantee business success, it must also incorporate performance evaluations to ensure the objectives are met.

Researchers further suggested that what matters the most is that organizations must combine all practices into a coherent bundle to create a better work environment in order to maintain employee satisfaction and gain competitive advantage (Armstrong, 2006; Cardon & Stevens, 2004; Sharma, 2009; Sung & Ashton, 2005; Terpstra & Rozell, 1993). In addition, it is worth mentioning that the configurational theory proposes that there are multiple, equally effective ways that can go hand-in-hand with delivering the same desired outcome (Wilkinson & Johnstone, 2016).

3.9. Evidence of the Configurational Theory

Configurational theorists have sought to investigate the relationship between HR practices and business performance. For example, Delery and Doty (1996) compare practices within two configurational systems, namely market-based and in-house systems. The results of the analysis indicated that there is some positive relationship between the staffing bundles and firm performance, particularly in terms of return on assets (ROA) and return on equity (ROE). The positive link between HR practices and business performance appearing in most of the models were contingent compensation, extensive training, careful selection and involvement. MacDuffie (1995, p.201) also suggested that in his research, the workforce will only exercise discretionary behaviours when they “believe that their individual interests are aligned with those of the company and that the company will make a reciprocal investment in their well-being”. The findings of the analysis indicated that flexible manufacturers with team-based systems, reduction of status barriers between management and employees, and investment in workforce training consistently outperform traditional mass production manufacturers. Researcher also concluded that variables capturing two-way and three-way interactions among the bundles of HR practices are even better predictors of performance (MacDuffie, 1995).

Besides, Ketchen et al. (1997) carried out a meta-analysis by aggregating 40 configurations-performance studies. Researchers suggested that the configurational theory does enhance performance and in particular for organizations that have broad sets of organizational dimensions. Results of the analysis also revealed that those studies which were focusing on a single industry had also experienced a greater imparts effect. However, researchers did not find any support that a specific combination of practices would enhance greater business performance (Delaney & Huselid, 1996).

In addition, serval studies provided rather mixed results, Gooderham et al. (2008) examined the relationship between HR practices and organizational performances from over 3,200 companies located in Europe. The results indicated that five of the six bundles 'control practices' such as assessing performance towards the individual or at the team level have a significant impact on performance, and two of the three bundles 'intermediary practices' such as career development and downsizing methods also have a significant impact on performance. However, none of the six bundles of 'commitment-based practices' has any impact on organizational performance. The results further proposed that the overall effect of HR practices on performance is relatively modest (Gooderham et al., 2008). Similarly, when Stavrou and Brewster, (2005) evaluated the possible bundles of HR practices over 3700 companies within the EU. Their results suggested that only seven bundles are significantly related to performance, six of which have a positive and one of which has a negative relationship with performance (Stavrou & Brewster, 2005).

Based on the above review of configuration approaches, it has been suggested that there are multiple equally effective bundles of practices that can work in tandem to achieve the same desired outcome (Wilkinson & Johnstone, 2016). Therefore, organizations should tailor HR practices based on the concepts of vertical and horizontal integration (Delery & Doty, 1996), where vertical integration refers to the need for HR practices to align with organizational goals, and horizontal integration refers to the fact that all HR practices and activities must work together to improve organization performance.

Connections between the SHRM and other models

4.0. Introduction

The above sections have explained how the different approaches contribute to the idea of HPWS and its relationship to SHRM. This advent of the SHRM field, including HPWS, is devoted to exploring the role of HRM in supporting business strategy, providing an avenue to demonstrate its value to the company. The SHRM literature suggests that HPWS is a good way for organizations to increase the efficiency of their daily operations. By producing a wide range of capabilities and behaviours, many of the components of HPWS can be viewed as a way of SHRM to promote an organization's flexibility (Datta et al., 2005). Specifically, these practices, systems, and approaches can not only facilitate workforce development, but also contribute to employee performance, loyalty, commitment, and motivation, which is an important aspect for an organization to achieve competitive advantage (Boxall & Macky, 2009; Patel & Conklin, 2012). Empirical evidence from the SHRM literature also suggests that HPWS enable employees to gain higher levels of skills and motivation and ultimately improve their performance through the use of a set of practices (Guthrie et al., 2009). In this section, the theoretical rationale is to explain SHRM from the perspective of the company's ability, motivation and opportunity (AMO) and business scorecard (BSC). Specifically, it is assumed that a firm can only achieve sustainable competitive advantages if it can leverage resources that are unique, valuable, rare, inimitable, and non-substitutable (Barney, 1991). It is believed that the link between the use of HPWS and business performance depends on the company's ability to create and allocate value-added resources to differentiate itself from its competitors (Messersmith & Guthrie, 2010). Therefore, researchers proposed that human resources, perhaps more than any other resources in the company, could be considered as the main element that meets these criteria (Wright et al., 2001).

5.0 Overview of the AMO model

The AMO model is one of the most popular models in the theory of SHRM (Bach & Edwards, 2005) and it shares many similarities with the HPWS (Raidén et al., 2006). The main premise running through this thesis is that HPWS relies on positive employee responses (e.g., Godard, 2004; Delbridge, 2007; Macky and Boxall, 2007). Job performance is influenced by team performance, which in turn is preceded by individual job performance as a function of the interplay of employee competence (A: Ability), discretionary effort (M: Motivation), and performance opportunities (O: Opportunity) (Boxall & Macky, 2009). The question is: Do the benefits to workers (e.g., perceived autonomy, skill development, and wage increases) actually outweigh the costs to them (e.g., work stress and work-life imbalance), so that individual workers are motivated to improve their skills and make additional performance efforts when the opportunity arises? (Boxall & Macky, 2009) Thus, in many leading studies, evaluating the impact of HPWS performance depends on having relevant data on firm and worker outcomes (e.g., Appelbaum et al., 2000; Boxall & Macky, 2009; Vandenberg et al., 1999).

The AMO model was originally proposed by Bailey (1993) and developed further by Appelbaum et al. (2000), which emphasizes that firm performance depends on individual ability, motivation, and opportunity (Hutchinson, 2013). The key idea is that the AMO model underlines the importance of choosing the right HR practices that belong into one of three primary dimensions: “skill-enhancing HR practices”, “motivation enhancing HR practices”, and “opportunity enhancing HR practices” (Appelbaum et al., 2000; Kellner et al., 2019; Lepak, 2006). If these three conditions are present within an organization’s practices, then there is a good chance that organizational performance will improve (Choi, 2014; Liao, 2005), and it can be expressed as:

$$\text{Performance (P)} = f\ (A, M, O)$$

However, researchers also emphasized that if one of these three features are missing, performance can be suppressed (Boxall & Purcell, 2003; Ichniowski et al, 1996; Liao, 2005; MacDuffie, 1995; Siemsen et al., 2008). In other words, the AMO model provides a framework for managers to identify the ideal HR practices to achieve higher performance on the basis that:

1) The workforce has the essential knowledge, capabilities and skills to complete a task (Boselie, 2010; Choi, 2014). For example, during a recruitment and selection process, managers are required to conduct extensive searches and evaluations to identify whether such individuals can perform well within the organization, assuming that the company operates in a competitive environment and is constantly facing new challenges. Managers also need to provide appropriate training and development programmes to the workforce to ensure that the workforce is capable of dealing with uncertainty. This is why researchers emphasized that accurate recruitment and selection process is critical for the AMO model (Huselid, 1995; Appelbaum et al., 2000).

2) HR managers must use a variety of HR practices to ensure that employees are motivated to perform well. Motivational techniques can relate to both extrinsic and intrinsic rewards (e.g., feedback, performance-based pay, performance appraisal, job security, work-life balance, career development and performance evaluations) (Boselie, 2010; Choi, 2014). Researchers believe that employees will ultimately perform better if

managers are willing to use these HR practices listed above to create a trustworthy and encouraging environment.

3) Last but not least, organizations should provide the necessary opportunities for future development and allow employees to participate in the organization's decision-making process. The key idea here is to ensure that employees are feeling a sense of involvement, and participation, which improves their well-being (Appelbaum et al., 2000). One of the ways to showcase this is by allowing the workforce to create a self-managed team whereby the decision-making process should be decentralized (Wood & Wall, 2007). Other opportunity examples include teamwork, social networks, autonomy, information sharing, involvement in decision-making and participation.

5.1. Evidence of the AMO model

In a study conducted by Bos-Nehles et al. (2013), researchers combined the additive and multiplicative approaches to examine the effect of the AMO model. The findings revealed that only the "ability" factor is the best predictor in predicting performance, while "motivation" and "opportunity" only marginally affect the business performance. Similarly, Innocenti et al. (2011) study also provided rather a mixed result. Researchers examined over 8,900 employees from 46 Italian organizations about how trust could influence the relationship between the AMO model and employee attitudes. The results of the analysis showed that the degree of managerial accountability significantly increase the effectiveness of incentives in fostering positive employee attitudes toward the organization, while such effectiveness is significantly lower when comparing HR practices to employee skills or opportunities.

Although AMO has been widely cited and used as a framework in academic research, its application effectiveness has been criticized due to insufficient empirical testing. The main reason is that most studies suffer from inconsistencies in the choice of dependent and independent variables (Kellner et al., 2019; Renwick et al., 2013). The selection of practices and performance measures across studies also makes it difficult to draw definitive conclusions about which practice(s) and method(s) play a critical role in performance (Kellner et al., 2019; Renwick et al., 2013). For example, in the studies by Lertxundi and Landeta (2011) and Sarikwal and Gupta (2013), the practice of "information sharing" was used as a motivational factor, while in the studies by Bello-Pintado

(2015) and Lee et al. (2019), the practice of "information sharing" was considered an opportunity dimension (Kellner et al., 2019). Similarly, "work-life balance" policy was used as a motivational factor in the studies by O'Donohue and Torugsa (2016) and Sarikwal and Gupta (2013), while it was used as an opportunity-enhancing factor in the studies by Fabi et al. (2015) and Kundu and Gahlawat (2016). Other variables such as "performance appraisal" and "communication skills" have also been applied differently across research. Table 3 provides a summary table showing how individual researchers select and view practices differently based on ability, motivation, and opportunity factors.

Table 3: Examples of selection practices and performance measures

	Information sharing	work-life balance policy	Performance appraisal	Communication skills
Ability enhancing factor			Sarikwal and Gupta, (2013)	Lee et al. (2019)
Motivation enhancing factor	Lertxundi and Landeta, (2011); Sarikwal and Gupta, (2013)	O'Donohue and Torugsa, (2016); Sarikwal and Gupta, (2013)	Fabi et al., (2015); Lee et al., (2019); Ogbonnaya and Valizade, (2018)	Lertxundi and Landeta (2011); Tregaskis et al. (2013)
Opportunity enhancing factor	Bello-Pintado, (2015); Lee et al. (2019)	Fabi et al., (2015); Kundu and Gahlawat, (2016)	Raidén et al. (2006)	

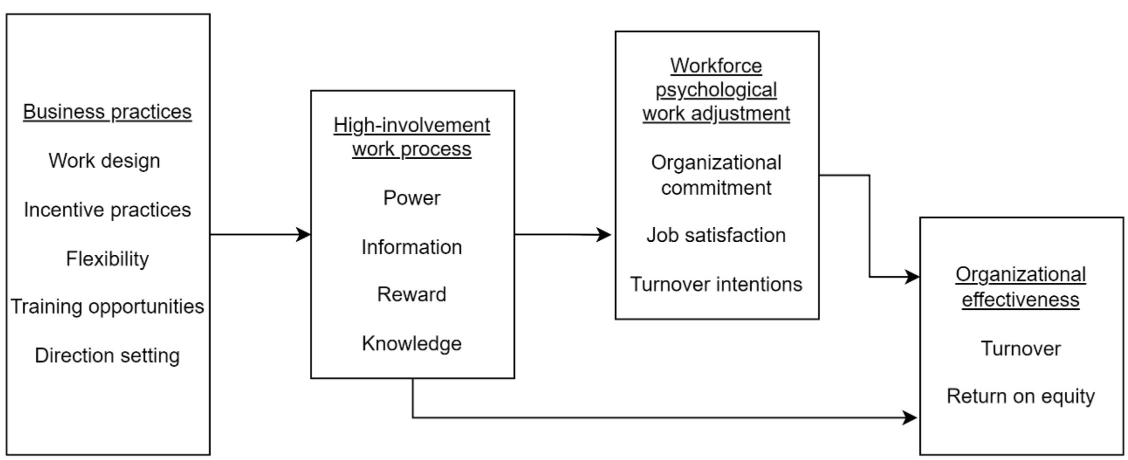
Beyond that, some researchers have also pointed out that the way each dimension of AMO affects organizational performance is more complex than simply categorizing HR practices into categories (Ehrnrooth & Björkman, 2012; Lepak et al., 2006; Marin-Garcia & Tomas, 2016), as it also depends on many other internal factors. For example, the employees' subjective perceptions of each of the HR practices. Or, which HR practices should be included in the bundle. Or, what is the best possible way for managers to implement the HR practices. (Ehrnrooth & Björkman, 2012; Marin-Garcia & Tomas, 2016). Besides, some of the most compelling results of the AMO model came from qualitative research, in which they were based on managers' intuitions about what might influence performance, rather than quantitative measurements (Currie et al., 2015: Purcell et al., 2003; Wood et al., 2015).

5.2. HRM-Performance-Link

In drawing on the conceptual model of Vandenberg et al. (1999), the researchers argue that business practices are related to participatory processes (e.g., HPWS) and, by extension, to workers' psychological states and measures of organizational effectiveness (Figure 1). Based on their findings, it is believed that

HPWS (e.g., universalistic, contingency, and configurability) not only increase the chance of a workforce's to achieve "greater advantage in skills and abilities" but also provide additional benefits to their motivational pathways as HPWS increase "worker satisfaction and other affective responses" (Vandenberg et al., 1999, p. 304). This idea is also reflected in Batt's paper, where the researcher argues that HPWS contributes directly to workforce skill levels and firm-specific knowledge, and indirectly to employee motivation, satisfaction, and retention levels (Batt, 2002). In other words, the direct pathway is important in ensuring that employees are able to perform more effectively individually and collectively. The indirect path, on the other hand, involves the cognitive psychology that the workforce is ready and continues to take ownership.

Figure 1: Conceptual model of high-performance work system

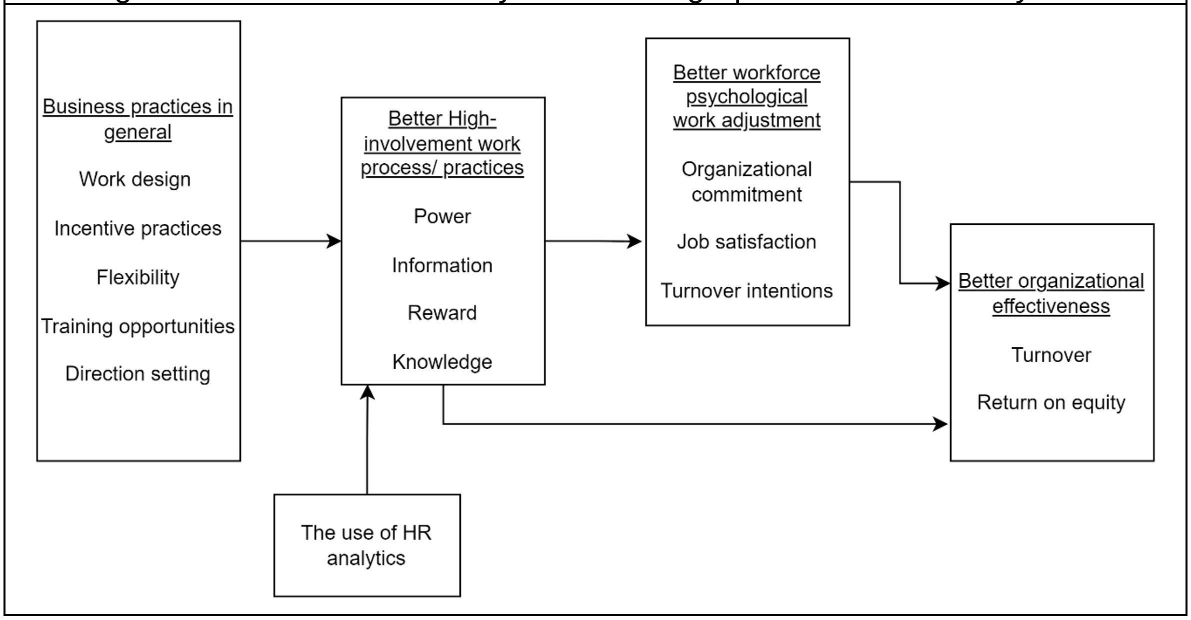


Source: Vandenberg *et al*. (1999: 307)

In addition, Boxall and Macky (2009) further suggest that HPWS enables employees to make more decisions, improves the information and knowledge they need, and rewards them for doing so. Indeed, this is consistent with the lens of the AMO framework (see above section): in order for the high engagement model (i.e., HPWS) to work, it must have a positive impact on employees' skills, motivation, and opportunities to contribute. Improved knowledge improves skills, while empowerment and information improve opportunities to contribute (Figure 1). Rewards are a direct attempt to increase motivation, which can also be improved by empowerment (i.e., more autonomy at work), information (i.e., feeling more informed) and knowledge (i.e., improved skills) (Boxall & Macky, 2009).

Building on this concept and model proposed by Vandenberg et al. (1999). This thesis aims to highlight the benefits of using HR analytics to consolidate managers' decisions (Figure 2). Specifically, both direct and indirect pathways can be enhanced, providing organizations with another way to identify and select which desirable practices should work based on the organization operating environment. It is important to note that developing and assisting smarter work as a means of responding to more SHRM in the organization.

Figure 2: The use of HR analytics within high-performance work system



6.0. Study Three Hypotheses

Before moving directly to the hypotheses, it is important to note that the dependent variable in HPWS (i.e., organizational performance) is relatively complex. In fact, some researchers believe that it is difficult to determine exactly what "performance" is. This is because the term itself is an "omnibus term, similar to organizational effectiveness" (Boxall & Macky, 2009, p.5), and it can be conceptualized in a variety of ways, including short-, medium-, and long-term economic outcomes, as well as broader notions of social legitimacy or corporate social responsibility (Edwards and Wright, 2001; Paauwe, 2004; Boxall and

Purcell, 2008). However, most researchers on HPWS have focused on economic performance criteria, as Godard (2004) points out in his evaluation of HPWS research. This means that the HPWS must be primarily cost effective to be considered successful. If the financial benefits do not outweigh the costs, then HPWS does not make economic sense for the company (Boxall & Macky, 2009). In other words, HR technologies such as HR analytics should not only contribute positively to HR efficiency, but ultimately to business performance as well.

With respect to the construction of the independent variable in HPWS, it is widely believed that the idea and perception of "best practices" without consideration of a specific context is therefore fundamentally controversial. Work systems, organizational culture, and employment practices vary significantly across occupational, hierarchical, workplace, industrial, and societal contexts (e.g., Appelyard and Brown, 2001; Lorenz and Valeyre, 2005; Kalleberg et al., 2006). Any claim in the literature that there is some general consensus on a system of best practices is patently false, and claims that a particular set of practices is naturally high-performing are untenable (Wood, 1999; Marchington and Grugulis, 2000; Bryson et al., 2005). Thus, to make real theoretical progress, this work must go beyond generating lists of practices and attempt to identify the processes and mediating variables (i.e., HR analysis) that are thought to influence a set of practices (Becker and Gehart, 1996).

6.1. Employee motivation

Employee motivation refers to satisfying the needs of employees using different ways to fulfil employees' determinations and desires. The process of motivation is a way of ensuring that employees are happy and in a positive state to help organizations achieve goals. In other words, motivation is an incentive method that encourages employees to work more proactively by formulating a set of HR practices and policies that enhance a better employee-firm relationship, and ultimately create a better chance of achieving the competitive advantage (Landry, et al., 2017; Paauwe & Farndale, 2017). If the employees in an organization feel that their performance and work results are not properly considered and evaluated, employees might build up negative feelings towards the firm, which affect the development and progress of the company. On the contrary, when employees' performance is well looked after with appropriate incentive plans, employees' creativity and innovative spirit can be fostered (DeCenzot et al., 2016) The employees' job satisfaction will likely be improved which further stimulates enhancement of the business performance. Moreover, motivation can also strengthen the good behaviour and performance of employees, increasing employee loyalty to create a cohesion force, which contributes to maintaining the stability of the company (Stone et al., 2020). In addition, as employees' sense of responsibility increases, they will take the initiative to solve problems and difficulties in their work, promoting coordination and cooperation among units, emphasizing the people-oriented development concept and creating a harmonious corporate atmosphere (Krishna & Aquinas, 2004; Sharon & Swapnalekha, 2015). Multiple studies have shown that HR practices, such as an effective performance appraisal system, are positively significant with employee motivation (Idowu, 2017; Van de Voorde et al., 2011). As a result, we believe that different types of variable pay systems would motivate employees differently. For instance, variable pay linked to team performance might be more likely to encourage employees to share ideas when compared to variable pay linked to individual performance.

In addition, the human resources department is considered to be the single most important department in any organization. This is because without a high-performing workforce, the success of any organization will be compromised. Therefore, managers need to ensure that the workforce is satisfied, committed and motivated. Evidence also shows that good behaviour and employee performance is associated with employee motivation, and by increasing employee motivation within the idea of SHRM, it leads to better loyalty and creates a sense of cohesion which helps to keep the company stable (Stone et al., 2020). Therefore, we hypothesize that:

Hypothesis:

H1: The higher the motivation of the workforce, the better the firm's financial return is, as higher motivation level strengthens the good behaviour and performance of employees, increasing employee loyalty to create a cohesion force, which contributes to maintaining the stability of the company (DeCenzot et al., 2016; Stone et al., 2020).

6.2. HR analytics

Regarding HR analytics, it is a tool that translates data into HR topics that can assist managers in selecting high performers, reducing recruitment costs, and better managing the workforce (Bughin et al. 2017; Collins et al. 2017; KPMG 2013; Kukde 2016; PwC 2020). According to a report published by Deloitte, "HR analytics is a business discipline that supports everything from operations and management to talent acquisition and financial performance" (Collins et al., 2017, p. 7). KPMG (2013, p. 2) said that "HR analytics can provide a tangible link between your people strategy and your organization's performance." Considering the above literature and reports, HR analytics can not only consolidate managers' decisions and increase transparency, but also reduce the complexity of an organization's HR practices.

However, it is important to note that the introduction of HR analytics might causes a disruption in traditions and well-known HRM practices and therefore there is resistance to implement HR analytics if uncertainty avoidance is high. As explained now, the former effect is particularly evident for performance management and since we are concentrating on the use of HR analytics to monitor the performance of employees relevant. Therefore, we hypothesize that:

Hypothesis:

H2: The more complex the HR department an organization has, the more it needs to use HR analytics to monitor employee performance, as HR analytics act as a tool to better manage HR-related matters and ultimately influence a firm's financial performance.

6.3. Variable pay systems

The use of variable pay in companies has a long history. Variable pay or variable rewards are monetary bonuses which is paid to the performance of an employee, a team, or an organization. It is believed to be a way to encourage employee behaviour by linking pay increases to an assessment of individual performance, usually measured against preagreed targets (CIPD, 2020). As variable pay is based on a performance measure, employees' earnings are expected to fluctuate up and down (Armstrong & Murlis, 2007). As a matter of fact, the fluctuation of variable pay is particularly welcomed by management because it converts a portion of the organization's fixed costs into variable costs, thus reducing expenses when performance declines (Robbins et al., 2009). It is important to highlight that those results of empirical research on the direction of the effects of these contextual factors are often ambiguous (CIPD, 2020).

According to Suff and Reilly (2004), companies with profit-sharing practices tend to outperform non-profit-sharing companies on a variety of corporate performance measures such as profit, corporate growth, and investor return. Based on a meta-analysis study published by Jenkins et al. (1998), researchers evaluated over 3000 cases and concluded that financial incentives such as variable pay showed a moderately strong positive relationship with individual performance, in which ultimately influence firm profit. Similarly, Cameron and Pierce (1994) evaluated over 90 experiential studies comparing rewarded with unrewarded control groups on four measures of intrinsic motivation. Results indicated that the relationship between intrinsic motivation and performance was positive, modest, and significant when extrinsic incentives (e.g., financial payments, prizes, and credits) were not offered. When extrinsic incentives were offered, the relationship between intrinsic motivation and performance was even stronger. Besides, Nyberg et al. (2015) examined the relationship between incentives and concurrent and future performance among nearly 12,000 workers over a five-year period, and the results of the analysis showed that incentives such as merit and bonuses were positively associated with workers' future performance. Other studies such as Lazear, (1996) and Heywood et al. (1997) as well as the OECD (1995) also provided evidence that variable pay increases the productivity of the company as a whole.

On the other hand, some studies have found no correlation between variable compensation and firm profits. For example, Poole and Whitfield (1994), in examining various measures of economic performance, found that there was no discernible relationship between financial participation schemes and return on gross profit. Similarly, Blanchflower and Oswald (1988) examined the Workplace Industrial Relations Survey (WIRS) from the UK and concluded that they could find no evidence that establishments with profit-based compensation achieve better financial performance.

In addition, companies with a high proportion of fixed costs are more sensitive to the economic environment. For example, the profit margin of a company with high fixed costs is drastically affected when sales decline during an economic downturn. In other words, fixed costs are more likely to affect a company operation compare with variable costs, and any increase in fixed costs in a company would affect the company's financial performance. Variable costs (i.e., variable pays, bonus and salaries), on the other hand, are costs that are directly related to performance and therefore change depending on employee performance. These costs can increase or decrease depending on performance, giving the company the flexibility to adopt different situations. Therefore, we hypothesize that:

Hypothesis:

H3: The higher the proportion of variable pay in a company, the higher the probability that the company will generate a profit, as variable pay converts a portion of the company's fixed costs into variable costs, thereby reducing expenses when performance declines (Robbins et al., 2009).

7.0. Employees' Motivation, HR Analytics and Variable Pay System

It is clear that variable pay (Cameron & Pierce, 1994; Heywood et al.,1997; Lazear, 1996; Nyberg et al., 2015) can increase employee motivation and satisfaction, which helps companies increase productivity and ultimately achieve better financial return. With a highly motivated workforce (DeCenzot et al., 2016; Stone et al., 2020; Van de Voorde et al., 2011), companies are more likely to retain their employees, increase their loyalty and productivity.

The main idea here is to investigate whether HR-related technologies such as HR analytics can strengthen this relationship (see paragraph above). By better and more accurately assessing employee performance, managers could make fairer and more accurate decisions when awarding variable pay (i.e., increase transparency about manager decisions) and thus increase employee motivation and satisfaction. Therefore, if employee motivation and satisfaction remain or increase to an optimal level, a better firms' financial performance can be expected.

In other words, the interaction analysis is trying to identify whether there is an additional effect generated between variables (Jaccard et al., 2003). As it implies that the mechanisms explaining the effect of "variable pay system" and "employee motivation" on the company's financial performance may differ depending on whether the company uses HR analytics to monitor employee performance. Therefore, we hypnotise that:

H4: The interaction effect between HR analytics, variable pay systems, employee motivation and a firm's financial performance is expected to be significant. Specifically, the interaction effects should go beyond the individual main effects of the variables involved (i.e., as HR analytics acts as a tool to provide more accurate variable pay to the employee, indirectly motivating them to perform better).

7.1. Training and development

Training and development (C1) is one of the most important human resources functions that must be reviewed regularly to motivate employees and foster a positive learning culture (DeCenzo et al., 2016). It can be described as a systematic approach to improving the effectiveness of individuals, teams, and organizations through learning and development (Marchington & Wilkinson, 2005). It is an area not only related to employee performance but also related to employee motivation (Amos et al., 2009). In addition, the training and development program should also be consistent with the department's objectives and take into account the determination of the employees. For example, a training program for the marketing department would be very different from a finance department.

Based on a study published by Kilpatrick (1997). The researchers examined the relationship between financial performance and training in agriculture using the Australian Agriculture Financial Survey (AAFS). Results showed that large and small farms managed by individuals participating in training often experienced greater profit growth than other farms with similar asset values. However, Aragón-Sánchez et al. (2003) pointed out that the results of their study, which used a sample of over 450 European SMEs, provide only some evidence of significant relationships between training and performance.

7.2. Employee engagement

Employee engagement (C2) is another important area for HR leaders to pay attention to. The CIPD refers to employee engagement as a "broad area of people strategy, and refers to narrower constructs such as work engagement or organisational commitment" (CIPD, 2021, p.25). Kahn (1990) describes the term as when an organization seeks to increase organizational value by involving employees in decision making and focusing on how people physically, cognitively, and emotionally express themselves when interacting with their work (Kahn, 1990).

Based on a meta-analysis study published by Harter et al. (2002). The researchers examined the relationship between employee satisfaction, employee engagement and financial performance using 7900 samples from 36 companies. The results showed that employee engagement can increase company profitability. Specifically, it can strengthen customer satisfaction, loyalty, and employee retention, with the company achieving a 4% higher profit than its competitors. When the Gallup Consultant Group analysed performance differences among 112,000 teams with more than 2.7 million employees in 276 organizations across 54 industries and 96 countries, the benefits of employee engagement were also clear. The results showed that employee engagement has a major impact on business performance, with the companies having the highest employee engagement performing significantly better than those with the lowest engagement. For example, the company with the highest employee engagement has 23% higher profitability, 43% lower turnover rate, and 18% higher productivity (Harter, et al., 2020). It can be inferred that employee engagement has an important impact on the company. In companies with high employee engagement, employees highly recognize the company, agree with the company's values and social norms, and are willing to work hard to achieve the company's goals.

7.3. Firm size

In general, it is assumed that larger companies tend to be more profitable than their smaller counterparts (Lee, 2009). This positive relationship between profit and firm size (C3) is supported by economic theory, which assumes that a larger-than-average profit can be achieved by expanding a firm in a sufficiently large economic market (Hirsche, 2016; Dahmash, 2015; Alexander, 1949; Stekler, 1964; Hall & Weiss, 1967; Scherer, 1973) as a larger firm can benefit from greater bargaining power, economies of scale, and sharing of resources at lower costs (Hirsche, 2016). The term “firm size” simply refers to the degree of organization of a firm. A distinction is usually made between small, medium, and large enterprises, with a workforce of fewer than 50 people is considered a small enterprise, less than 250 people considered a medium enterprise, and anything over 250 people a large enterprise (European Commission, 2021).

Amato and Burson (2007) attempted to answer this important question by examining the relationship between firm profitability (i.e., return on assets) and firm size in the financial industry. They concluded that there are profit opportunities for both small and large firms, but that medium-sized firms are not able to compete with small and large firms in terms of profitability. The idea behind this concept is that smaller companies can operate in a niche market and specialize in a single product or a few services while large companies can take advantage of economies of scale and their bargaining power. Researchers found that medium-sized companies are often stuck between the two spectrums and are neither able to compete in a niche market nor achieve perfect economies of scale (Amato & Burson, 2007). Similarly, the results of Amato and Amato (2004), who examined more than 1250 firms in a standard structural performance model for different firm sizes, also suggested that there is a nonlinear relationship between firm size and profit rates. This may be due to the fact that some other factors such as market concentration, entry barriers, and consumer behaviour are considered more important than firm size (Lee, 2009). In addition, Akhigbe and McNulty (2005) put a special focus on the profitability of European banks and found that there is a significant profit difference between them. It was found that the smaller banks receive the least profit, while the international banks receive the lion's share. Across the banking sector, all banks were able to generate higher profits each year as the number of shareholders and the value of market share increased (Akhigbe & McNulty, 2005).

7.4. Firm age

The relationship between firm age (C4) and profit remains a controversial topic among many scholars. Coad et al. (2013) suggested that a firm's profitability varies according to its age. Researchers studied more than 62,000 Spanish manufacturing firms from 1998 to 2006 and found that a firm's performance tends to improve with age, as mature firms appear to have better market knowledge that allows them to steadily increase productivity without affecting the firm's capital structure. Similarly, Ilaboya and Ohiokha (2016) examined the relationship between firm age, firm size, and profitability using the theory of "learning by doing". The study includes over 200 observations in 30 companies over a six-year period, and the researchers found that there is a significant positive relationship between company age, company size, and profitability. It is also important to note that the results of Majumdar's (1997) study showed that younger companies are less productive and more profitable, while smaller companies are less profitable and more productive.

7.5. Business ownership

When it comes to owning a business (C5), it is important to understand that different forms of ownership can have a different impact on business performance. A company owned by a group of board members would be very different from a company owned by the public. In general, a company's ownership can change depending on the business cycle and logical development, which means that balancing the relative values of different elements in the market can cause an organization to adjust its ownership. For example, a change in ownership may occur when a business owner decides to raise money to expand his or her business, and the amount of capital received depends on the degree of control the owner is willing to relinquish (e.g., control over the business, financial returns, and liabilities) (Carysforth & Neild, 2000).

In a study conducted by Westman (2011), the researcher investigated into how different ownership levels affect corporate profitability by including all listed and unlisted commercial banks and investment banks from 37 European countries. The result showed that management ownership has a positive impact on the profitability of non-traditional banks, while board ownership has a positive impact on the profitability of traditional banks (Westman, 2011). In addition, Fernandez et al. (2005) examined how bank ownership affects profitability in eight OECD countries. The results suggested that state-owned banks and mutual banks have higher interest margins than commercial joint-stock banks, but do not have higher net profits. Similarly, Gedajlovic and Shapiro (2002) and Li et al. (2007) found that different ownership structures affect the financial performance of firms differently. Based on these examples, it is reasonable to assume that ownership structure plays an important role in firm profitability.

7.6. Internal recruitment

Internal recruitment (C6) involves searching within the company for a qualified person to fill a specific position. This approach tends to be more common in larger companies because HR managers have a larger pool of talent from which to choose. In 2019, Harvard Business Review published a list of the top 100 chief executive officers (CEOs). Among the top 10% of CEOs on this list, internal promotion is the most common. Only the CEO of Iberdrola, Ignacio Galán, in the 6th place, was recruited externally (DeVaro, 2020). Researchers also point out that internal hiring can drastically reduce hiring costs compared to external sources. This approach not only allows the organization to save money, but also improves employee morale and motivation (DeVaro, 2020; DeNisi & Griffin, 2015) by signalling to employees that the organization values their work and achievements. Since the employee has already worked in the organization, managers should have enough knowledge about the employee's strengths and weaknesses. Less guesswork is required when evaluating his or her abilities for another position. In addition, current employees are more familiar with the organization's culture, practices, and procedures, while external applicants must spend time adjusting and fitting in. Overall, evidence showed that internal recruiting typically provides more accurate data on current staffing levels, which reduces the risk of hiring the wrong person, brings stability, and ultimately increases the company's financial viability (Andrews, 2009; Sims, 2002).

7.7. Employee turnover

Another control variable worth including is the idea of employee turnover (C7). It simply refers to employees leaving an organisation (Phillips & Connell, 2003). This process usually impacts organisation spending, which influences the time and money spent on new recruitment. (e.g., low productivity of new employees, customers acquisition cost tend to be higher while new employees come up to speed) (Phillips & Connell, 2003). For instance, Ban et al., (2003); Glebbeek and Bax (2004); Meier & Hicklin, (2008); Siebert and Zubanov (2009).

Besides, in a study conducted by De Mesquita and De Aquino (2015), the results of the analysis demonstrate that lower employee turnover can lead to better financial returns (i.e., higher revenue). The researchers also suggested that the impact of employee turnover could cost the company at least $2 million per year (or about 1.35% of annual gross revenue). Similarly, Kacmar et al. (2006) examined whether turnover affects unit performance using a sample of 262 Burger King stores. The results also showed that turnover does indeed affect unit-level performance, both on sales and profits. However, in a study published by Lee (2018), the researcher examined how various employee turnover, namely employee turnover, termination, and involuntary turnover, affect performance. Based on the findings, Lee (2018) challenges the widely held belief about the detrimental effects of employee turnover on organizational performance and suggests that turnover can also bring benefits to organizations. The results of the analysis showed that there is a clear nonlinear pattern with an inverted U-shaped relationship between employee transfers and involuntary turnover, while involuntary turnover has a linear positive relationship with firm performance. In other words, these results ultimately suggested that firm performance has different outcomes depending on the type of employee turnover.

7.8. Research and Development

The pursuit of profit maximization under fixed conditions is the main goal of any company, and research and development (R&D) (C8) could be one of the most important means to help organizations achieve this goal. R&D is a term commonly used to refer to the part of a company that specializes in exploring ideas that are not yet mature (Golder & Mitra, 2018). It is the driving force for the advancement of company products and services which help accelerate product improvement that increases financial value. In other words, the R&D department seeks to improve all phases of operations (e.g., reducing costs and improving economic efficiency) within a given timeframe to ensure that their company remains competitive in the marketplace (Vlachvei, et al., 2016; Welfens, 1999).

In terms of the HRM context, one can refer to the fundamental ideas driven by the company's business concepts and HRM objectives and translated them into research and development activities as a means to achieve HRM objectives. Using a sample of 55 publicly traded companies operating in the pharmaceutical industry between 2005 and 2014, Jaisinghani (2016) examined the dynamic relationship between R&D intensity and corporate profitability. The conclusion is that R&D contributes to an increase in corporate profits in both return on assets and return on sales. In particular, productivity, profit levels and profit margins are significantly higher than for companies that do not engage in R&D. Similarly, in a study published by Vurur and Ilarslan (2016), researchers examined the relationship between R&D spending, gross profit, and operating profit of one of the largest pharmaceutical companies in Turkey. The results also showed that there was a positive relationship between R&D spending and operating profit.

7.9. Job autonomy

In the face of the global pandemic, companies have adapted their working style to cope with the situation, and one of these ways is the so-called job autonomy (C9). Job autonomy means that a company's employees have the freedom to determine their own work structure (e.g., work methods, procedures, times and locations) without intervention from management or the company. This can bring numerous benefits, such as stimulating more creativity among employees and improving work-life balance (Oeij, et al., 2017). When employees have high autonomy, it undoubtedly reflects highly on employees' trust and affirmation from the organization, improving employees' sense of identity with the organization and their commitment to work. Besides, offering jobs with such attributes also leads to higher employee satisfaction and can become a recruitment strategy to attract talent.

Based on a statistical analysis study conducted by Preenen et al. (2016), the researchers examined the relationship between employee job autonomy, firm age and firm performance (i.e., sales, profits) over 3300 firms in the Netherlands. The results showed that job autonomy is positively correlated with a company's revenue growth and that this relationship is likely to be stronger for young companies. Therefore, the researchers suggested that it is particularly important for young companies to select a set of HR practices that promote a culture of workplace autonomy (Preenen et al., 2016). Similarly, in a survey of 302 teachers, researchers suggested that workplace autonomy and work-life balance have a significant impact on respondents' job performance (Johari et al., 2018). Therefore, we can assume that an employee with higher job performance can potentially generate more revenue for organizations. However, contrary to the common assumption that autonomy in the workplace is better for employees, Stiglbauer and Kovacs (2018) suggested that not every employee expects or needs the same level of autonomy. If an organization provides too much autonomy to its employees, it may create a sense of burden and reduce job satisfaction (Stiglbauer and Kovacs, 2018). Researchers emphasized that work autonomy can motivate employees and increase their productivity and satisfaction, but in an excessive state it can be counterproductive. In addition, the study indicated that autonomy levels should also depend on other characteristics such as organizational culture and employee working style.

7.10. Management- employee relationship

The term “employee relations” refers to the relationship between employees and management (CIPD, 2020). Employee relations (C10) are considered to be one of the most important elements influencing the development of the company (Gennard & Judge, 2005). Although strikes and other forms of industrial action have decreased over the past decade, conflicts between management and employees remain in any organization (CIPD, 2020). Therefore, managers must ensure that they treat employees with respect and fairness. When organizations are able to maintain a positive relationship between employees and management, it can attract and retain excellent employees, boost their morale and productivity, and ultimately improve organizational performance (Lyster & Arthur, 2007). In other words, building a harmonious relationship with employees can not only promote a positive work culture, strengthen the sense of teamwork and the idea of equality, but also create a good corporate image in society.

In a study presented by Oswald et al. (2015), researchers investigated into how employee well-being and satisfaction (i.e., the relationship between management and employees) could influence productivity in companies. The results showed that productivity is about 12% higher when employee well-being is well taken care of. In addition, Edmans (2011) and Edmans (2012) examined the relationship between employee well-being and the long-term stock market of the top 100 companies to work for in the United States. The results suggested that employees who are happy at the company tend to experience returns that are 2.3% to 3.8% higher than the industry average. Similarly, Samwel's (2018) findings showed that there is a positive relationship between employee relations and employee performance, and between employee relations and organizational performance. Based on the evidence above, we expect that the "climate" between managers and employees matters for the company's financial returns

7.11. Market competitiveness

Market competitiveness (C11) is a term that defines how competitive a market is, the number of suppliers or retailers competing to provide consumers with the goods and services would often act as a reference point to determine whether a market is competitive or not (Appelbaum, 1982; Nikaido, 2015). In other words, the competitiveness of the market also determine how difficult it is for a company to succeed. There are four types of market competitions, being perfect competition, monopolistic competition, Oligopoly competition and Monopoly competition (Dixit, 1984; Gillespie, 2014).

7.11.1 Perfect competition

Perfect competition is one of the market structures with a large number of firms. A market with perfect competition has the following four characteristics in particular:

(1) Equilibrium state: there are many suppliers in the industry, and the sales volume of each supplier accounts for only a small part of the total sales volume. There is no single supplier who can influence the price of the product or service. The price of the product is determined according to the supply and demand in the market (Brent, 2004).

(2) Product homogeneity: the products or services produced by each supplier in the market are homogeneous and do not differ from each other. Besides, consumers only pay attention to the price, and there is no subjective preference for individual suppliers (Brent, 2004).

(3) No barriers to entry and exit: all suppliers are free to enter and exit the market whenever possible (Forssbaeck & Oxelheim, 2014).

(4) Complete market information: Each supplier and customer has completed all the essential market information and is assumed to make rational decisions to maximize their self-interest (Brent, 2004).

7.11.2. Monopolistic competition

Monopolistic competition can be defined as the exact opposite of perfect competition, where the product and service are not homogeneous and there are few barriers to entry and exit (Gans et al., 2003). However, similar to perfect competition, monopolistic competition also have a large number of suppliers and consumers in the market, and no firm has complete control over the market price. In other words, a monopolistic competition is when there are many suppliers that produce products that are different from other but serve for the same purpose (McEachern, 2016). The products of these companies are interchangeable but differ from each other (e.g., in terms of brand and quality).

7.11.3. Oligopoly

An oligopoly is a form of market competition in which there are barriers to entry (e.g., economies of scale, patents, expensive and complex equipment), which means that only a few firms can operate in the market (Dransfield, 2013). Typically, there are a small number of large firms that supply products to a large number of consumers. Because there are only a few suppliers, various forms of collusion can occur in an oligopoly market, affecting competition in the market and ultimately leading to higher prices and a decline in quality (Dransfield, 2013; Free & Free, 2010).

7.11.4. Monopoly

Last but not least, a monopoly is a competitive market where only one supplier offers a product or service for which there are no close substitutes (Boone et al., 2019). The supplier can easily adjust its price and decide how much it is willing to offer consumers. It is generally believed that the main reason for a monopoly is barriers to entry (e.g., exclusive legal privileges, control of sources of supply, or patented products). Table 4 provides a overview of the different types of market competitiveness in different factors, such as number of supplier, product type, information transparency and barrier of entry.

Table 4: A summary of market competitive type

Market competitive type	Perfect competition	Monopolistic competition	Oligopoly competition	Monopoly competition
Number of Supplier	A lot of suppliers in this market	More suppliers than in the oligopoly market but less than in the perfect market	Not a lot of suppliers in this market, between two to twenty suppliers	Only one operate in this market
Product type	Identical product or service	There is difference in product quality or price	More or less the same, but might have some differences in product quality or price	Exclusive, unique and not be substituted
Information transparency	Fully transparent	Transparent but not as good as perfect competitive	Only few information but usually within the market	No information at all
Barrier of entry	Extremely easy, no	Easy	Difficult	Extremely difficult, high

	barrier			barriers to entry
Real example	Agricultural and foreign exchange markets	Hotel, restaurant and consumer service business	Car, airplane manufacturing and soft drink markets	Microsoft, Apple IOS and households water supplier markets

8.0. Dependent variable

For the dependent variable, question 69 have been selected. Specifically, it asked: “In 2018, did this establishment make a profit?”, and participants would be able to answer “Yes, we made a profit”, “No, we made loss”, “We broke even” and “Not applicable, our company is a not-for-profit organization” for this question. However, due to the nature of the research question, we excluded the variable “Not applicable, our company is a not-for-profit organization” as well as we have combined “No, we made loss” and “We broke even” into one variable.

8.0.1. Independent variables

As regards to our independent variables, for (H1), how employee motivation influences a company performance (i.e., financial return). We used answers to the question “Overall, how motivated do you think employees in this establishment are??” which were grouped into 4 categories, being “Not at all motivated”; “Not very motivated”; “Fairly motivated” and “Very motivated”. In order to evaluate how HR analytics might influence a firm’s financial profit (H2). We used question two3. “Does this establishment use data analytics to monitor employee performance?” which were “Yes” and “No”. Besides, in order to evaluate how different types of variable pay (H3) influence a firm’s financial profit, we used answers to the question “How many employees at this establishment received the following types of variable pay?”, 1) Payment by results, for example, piece rates, provisions, brokerages or commissions. 2) Variable extra pay linked to individual performance following management appraisal. 3) Variable extra pay linked to the performance of the team, working group or department. 4) Variable extra pay linked to the results of the company or establishment (profit-sharing scheme). For each question, answer categories are classified into 7 groups, being “None at all”, “Less than 20%”, “20% to 39%”, “40% to 59%”, “60% to 79%”, “80% to 99%” and “All”.

8.0.2. Control variables

For the first control variable (C1), it is about the frequency management offer training and development for their employees, we used question 28, “How often are the following practices (training and development) used to motivate and retain employees at this establishment?” which were “Very often”, “Fairly often”, “Not very often” and “Never”. Besides, the control variable (C2) is looking at how employee might influence on firms’ financial performance. We used answers to the question “Does this establishment make use of suggestion schemes?” (i.e., the collection of ideas and suggestions from the employees to make changes within the organization) and participants would be able to answer from one of the two following: “Yes” and “No”.

Furthermore, with regard to how firm size might influence firm performance (C3). We used answers to the question “Approximately how many people work in this establishment?” which were grouped into 5 categories, being 10-19 employees; 20-49 employees; 50-249 employees; 250-499 employees and more than 500 employees. For (C4) on the age of the firms, we calculated the year of operation using the answers to the question “Since what year has this establishment been carrying out this activity?” (i.e., year 2020 take away the number of establishments).

In terms of how ownership might influence a company’s financial performance (C5). We used the answer to the question “Since the beginning of 2016, has there been any change in the ownership of the company to which this establishment belongs?” and participants would be able to answer from one of the three following: “Yes, and it involved a change of management”, “Yes, but management remained the same” or “No”.

Another control variable is the internal recruitment (C6), we used the answer to the question “When recruiting, how often does management start by looking whether there are any suitable internal candidates?”. Participants would be able to indicate one of the following: “Always”, “Most of the time”, “Sometimes”, “Rarely” or “Never”. Moreover, with regard to (C7), it is looking at how turnover rate could potentially influence organizational profit. We used question 62 from the ECS to evaluate that: “How difficult is it for this establishment to retain employees?”. Management can select from “Not at all difficult”, “Not very difficult”, “Fairly difficult” or “Very difficult” for their answer. Moreover, when it comes to how research and development could influence firm performance (C8), we used “Is this establishment engaged in the design or development of new products or services?” which were “Yes, this is mainly carried out internally at this establishment”, “Yes, this is mainly carried out in collaboration with one or more other establishments within our company”, “Yes, this is mainly carried out in collaboration with one or more other companies”, “Yes, this is mainly contracted out” or “No”.

For job autonomy (C9), we used the following question from the ESC: “For how many employees in this establishment does their job include independently organising their own time and scheduling their own tasks?” which were “None at all”, “Less than 20%”, “20% to 39%”, “40% to 59%”, “60% to 79%”, 80% to 99%” or “100%”

Regarding to the “relationship” between the managers and employees (C10), we used answers to the question “How would you describe the relations between management and employees in this establishment in general?” by differentiating between “Very good”, “Good”, “Neither good nor bad”, and “Bad or very bad”.

With regard to the competitiveness (C11) of the market that a firm is embedded in, we used answers “Not at all competitive”, “Not very competitive”, “Fairly competitive”, and “Very competitive” to the question 66 “How competitive would you say the market for the main products or services provided by this establishment is?”

9.0. Method

The above section has focused on the dependent, independent and control variables of the study. The purpose of this section is to explain and discuss the methodology used. It begins with an introduction to the nature of the data and then goes into the logic of why the main effect and interaction were chosen for the analysis of the third research study. Ontology and epistemology are also discussed before the research findings are presented.

9.1. Nature of the thesis data

The data in this paper comes from the 2019 European Company Survey (ECS), which focuses on a different aspect of company operations (e.g., Houten & Russo, 2020) and covers 28 European countries and more than 20,000 company cases, including HR practices, skills utilization, skills strategies, digitalization, direct employee involvement, and social dialogue. The goal of the ECS is to help practitioners identify “bundles of workplace practices” that lead to outcomes that benefit both employees and employers.

9.2. Target population

The target population was all companies with ten or more employees in economic sectors operating in the market throughout Europe. Industries such as agriculture, forestry and fishing mining (A), quarrying (B), manufacturing (C), electricity, gas, steam and air conditioning supply (D), water supply, sewerage, waste management and remediation activities (E), construction (F), wholesale and retail trade, repair of motor vehicles and motorcycles (G), transportation and storage (H), accommodation and food service activities (I), information and communication (J), financial and insurance activities (K), real estate activities (L), professional, scientific and technical activities (M), administrative and support service activities (N), public administration and defence; compulsory social security (O), education (P), and human health and social work activities (Q) arts, entertainment and recreation (R) and other service activities (S), activities of the household (T) and activities of extraterritorial organizations and bodies (U) were all included in the ECS 2019.

Besides, the survey was conducted online and had to be tailored for different types of respondents, such as managers in a company with one or more plants or employee representatives acting as individuals or as part of a council or delegation. The characteristics of the respondents were also taken into account when formulating the questions. For example, for organizations that had been operating for less than three years at the time of the survey, any questions about events in the past three years were phrased to apply to the entire period of the organization's operation. This survey was adopted in this thesis because the ECS has the advantage that it includes a question on the use of HR analytics which is not commonly included in other datasets, most notably the CRANET dataset, which is frequently used in the field of international and comparative HRM. Specifically, the ECS data is representative for businesses and organizations with 10 or more employees throughout the EU and thus enables us to test our hypotheses on a large sample of countries with different institutional and market contexts.

9.3. Main and Interaction Effects

Scholars in the field of strategic HRM have consistently found that HR practices at the firm level are not the direct source of competitive advantage (Delery 1998; Becker & Huselid, 1998). Rather, it is the people who are selected, motivated, and developed through these HR practices (i.e., variable pay system) that increase competitive advantage (Messersmith & Guthrie, 2010; Wright et al., 1994). It is important to note that these organizational processes act as transmission links in which human capital (e.g., knowledge, skills, abilities), social capital (e.g., motivation, relationships), and employee behaviours (e.g., innovation and strategic congruent behaviour) interact with each other to improve organizational performance (Messersmith & Guthrie, 2010). In other words, these HR practices (i.e., HR analytics and variable pay system) act as a catalyst, helping managers clarify and understand the causal structure behind the relationship (Appelbaum et al., 2000; Drummond & Stone, 2007).

9.4. The Main Effect

A "main effect" simply means the effect of one of your independent variables on the dependent variable, ignoring the effects of all other independent variables (Krantz, 2019).

Main Effect #1: Variable pay system - Are there any differences in the firms' financial performance that can be attributed to the variable pay system?

Main Effect #2: HR analytics - Are there any differences in the firms' financial performance that can be attributed to the use of HR analytics?

Main Effect #3: Employees' motivation level - Are there any differences in the firms' financial performance that can be attributed to the Employees' motivation level?

9.5. The Interaction Effect

In terms of the interaction effect, it may occur when considering the relationship between two or more variables. The term "interaction" is used to describe a situation in which the effect of one variable depends on the state of the second variable (Alfes et al., 2013). This means that for a set of events represented by an observation space, the impact of the performance of one of the variables is assumed to depend (i.e., greater or weaker) on the performance of the corresponding other variables. The interaction effect is characterized by effects beyond the individual main effects of the variables involved.

The main idea of the interaction effect in this thesis is to provide the researcher with a method to determine whether the indirect effect is conditional on the value of a particular variable (Jaccard et al., 2003). This approach makes it possible to examine if the interaction effect changes as a result of the use of HR analytics. Thus, it implies that the mechanisms explaining the effect of “variable pay system” and “employee motivation” on the company’s financial performance may differ depending on whether the company uses HR analytics to monitor employee performance. That is, the impact of the use of HR analytics on HPWS. Therefore, based on this concept. In other words: To determine if variable pay system, HR analytics or employees’ motivation level influence the firms’ financial performance, this thesis needs to test for four different effects:

Interaction Effect #4: Is there an interaction effect between variable pay system, HR analytics or employees’ motivation level in determining the firms’ financial performance?

Effects #1, #2 and #3 are known as main effects because they are exclusively due to one factor or the other. In statistics, a main effect is the effect of only one of the independent variables on the dependent variable. The first step in determining whether the main effect results in statistically significant differences in the dependent variable is to calculate the marginal mean of each group. Therefore, by adding variables #1, #2, and #3 and analyzing them together results in an interaction effect

Hypothesis:

H4: The interaction effect between HR analytics, variable pay systems, employee motivation and a firm's financial performance is expected to be significant. Specifically, the interaction effects should go beyond the individual main effects of the variables involved (i.e., as HR analytics acts as a tool to provide more accurate variable pay to the employee, indirectly motivating them to perform better).

Summary of the main and interaction effect

The proposed research questions focus on the main and interaction effects between three variables, namely HR analytics, employee motivations, and variable pay systems (Rather than solely focusing on HR analytics). This is an important and relevant area of investigation because it is recognized that both employee motivations and variable pay systems can provide important competitive advantages. While the main effect of HR analytics on organizational performance is the direct impact that how the use of HR analytics has on organizational outcomes. This includes the ability to improve decision-making, enhance operational efficiency, and increase revenue.

The interaction effect looks into the relationship between HR analytics, employee motivation, and the variable pay system is also an important area of inquiry. The interaction effect refers to the combined impact of these three variables on organizational performance. The impact of analytics on organizational performance is likely to vary depending on the level of employee motivation and the type of compensation system in place. For example, the use of HR analytics may have a greater impact on organizational performance when employee motivation is high and a performance-based compensation system is in place

In summary, the research question three is focusing on the main effect and interaction effect between three variables (analytics, employee motivation, and variable pay systems) because it aims to understand the complex relationship among these factors that influence the overall performance of the organization. By considering all three variables together, the research can gain a deeper understanding of how they interact and influence each other. For example, analytics may improve employee motivation and productivity, but only when combined with an effective variable pay system. Similarly, a good variable system may not be effective if employees are not motivated because of the use of HR analytics. Therefore, studying the main effect and interaction effect of these variables will provide a more comprehensive understanding of the factors that influence organizational performance, and managers can better design and implement strategies that optimize the use of analytics to drive better organizational performance.

9.6. Logistic regression model

Because the dependent variable is dichotomous and it should reflect the predicted probabilities at " 0 " and " 1 ". If the company is marked as " 0 ", it means the company is not using HR analytics to monitor employee performance whereas if the company is marked as " 1 ", it means the company is using HR analytics to monitor employee performance. Therefore, the author decided to use a logit specification in the analysis. To test the hypotheses, it estimates the influence of each independent variable, adjusted for other variables. Furthermore, due to the ECS response being gathered from 28 EU countries, it cannot assume that the errors can be distributed independently. Since the dependent variable is a dichotomy, the effect should reflect the predicted probability (bounded by 0 and 1). Therefore, it appreciates a multi-level (logit) model that contains country-specific random sections, the estimate a *multilevel logistic model* which includes a country-specific random intercept that follows the form of:

$$\ln\left(\frac{p}{1-p}\right) = \gamma_{00} + \gamma_{10}X1_{ij} \dots + \gamma_{k0}Xk_{ij} + \gamma_{01}W1_j \dots + \gamma_{0k}Wk_j + u0_j$$

Where p is the probability that companies use HR analytics; γ_{00} is the conditional grand mean; $\gamma_{10}, \dots, \gamma_{k0}$ is the set of coefficients that consider firm-level variables $X1_{ij}, \dots, Xk_{ij}$; while $\gamma_{01}, \dots, \gamma_{0k}$ is the set of coefficients that consider a wider range of variables, for example at a macro-level $W1_j, \dots, Wk_j$. The coefficients can be evaluated as linear effects on the "log-odds" of using HR analytics. $u0_j$

represents the country-specific error for which the variance σ_{u0}^2 is estimated, and is assumed to be zero-mean normally distributed. The firm-level variance is implied by the binomial distribution. Moreover, based on the data set provided by the ECS, we noticed that ECS uses a stratified sample based on company size and industry, creating unequal probabilities of sample inclusion according to the value of these variables. We solve this problem by including sector and size as covariates in all estimated models to ensure that the errors are conditionally independent.

9.7. Standard error

The standard error provides information about the quality of the estimated parameter". The more individual values there are, the smaller the standard error, and the more accurate the unknown parameter can be estimated. It is important to note that every statistic has a standard error associated with it (Gravetter & Larry, 2016; Perry, 1995). A standard error of " 0 " means that the statistic has no random error. The representation of the population data, with the sample is closely distributed around the population. Meanwhile, the higher the number of standard errors, the less accurate the statistic and does not accurately represent the population data. In other words, the smaller the standard error, the more representative the sample will be of the overall population (Gravetter & Larry, 2016; Perry, 1995).

9.8. Log-likelihood

The log-likelihood value of a regression model is a measure of the model fit. The higher the log-likelihood value, the better the model fits the data set (i.e., the closer the negative value to zero) (Pampel, 2020). For example, a higher log likelihood value for one model (-90.00) than another model (-120.00) should indicate that the first model is a better fit to the data. In addition, the log likelihood value for a particular model can range from negative infinity to positive infinity (Pampel, 2020). It is important to note that log-likelihood values cannot be interpreted as fit indices alone, as they are a function of sample size (Halli et al., 1992; Ward & Ahlquist, 2018). Therefore, the likelihood values should be compared with the likelihood values of another model.

9.9. Ontology and epistemology

Before deciding which methodology to adopt for the thesis, it is important to be clear about the philosophical basis of the research idea. Specifically, these background assumptions inform the methods of data collection, analysis and interpretation of the thesis (Cordeiro et al., 2015). Both ontology (i.e., what is there for people to know, the reality and existence of things) and epistemology (i.e., how is knowledge created and what is possible to know) are two concepts that come from the philosophical perspective. They are based on the idea of how philosophers see the world, and in what form of belief is most appropriate for a particular context.

Ontology is about the idea of the nature of reality (Rawnsley, 1998; Urmson & Ree, 1989). Perhaps the most important question ontology addresses is whether the social phenomena we study should be understood as existing objectively (i.e., realism, objectivism) (Bryman & Bell, 2015; Cameron & Price, 2009). Or, is the element of object that can be manipulated by the activities of people (i.e., constructionism) (Bryman & Bell, 2015; Bell, et al., 2018; Cameron & Price, 2009). While epistemology is referred to how an individual understands knowledge, how they understand their own thinking process in a situation, and what does it mean to say that someone knows (Greene et al., 2016). In other words, epistemology addresses the question “How can I know reality?” (Audi, 2011; Keegan 2009). Moreover, within epistemology, there are also two different branches that are mostly relevant with business studies. Firstly, the belief that knowledge can be measured using reliable designs and tools as an outsider (i.e., positivism) (Brown, 2022). Secondly, the belief that reality needs to be interpreted to discover the underlying meaning (i.e., interpretivism) (Brown, 2022). And, when the thesis combines both the ontology and epistemology together, then the philosophers/ researchers would be able to get a holistic view of how to generate and understand knowledge (i.e., research paradigm).

Moreover, it is important point out that historically, social sciences research including HRM mainly relied on either qualitative or quantitative approaches (Leung; 2021; Pierce 2008). The differences between quantitative approach and qualitative approach were usually view as completely the opposite side of a spectrum. The quantitative approach followed the positivist paradigm, the objective here is to discover how organization's policy and regulation (e.g., HR practices) shape employees' behaviour. In other words, this research philosophy approach is frequently linked with scientific studies that are primarily data driven and follow statistical analysis (Lastrucci, 1963). While, the qualitative approach followed the interpretivist paradigm, in which the objective here is to find out how employees shape and interact with the organization from personal experience. The idea is that each individual are intricate and complex, different people might experience and view the same regulation (e.g., HR practices) differently.

Despite the differences of both viewpoints, it is still possible to combine these two methods and employ them in one research project to gain a much wider view of a specific topic (Ghiara; 2020; Leung; 2021; MacGregor & Cooper, 2022). According to Ghiara (2020), it is believed that the mixed methods approach should be a distinct paradigm itself, in which allowing both different combination of paradigms to general insights. Ghiara (2020) further suggests that members of mixed method community can adopt different ‘worldviews’ as they do in both qualitative and quantitative method communities. This debate highlights the pluralistic nature of social sciences research, and the importance toward researchers’ values, beliefs and assumptions (Ghiara, 2020). Similarly, Johnson (2011) also suggested that in social sciences research, most “scholars would identify themselves as ‘‘quantitative’’, ‘‘qualitative’’, or ‘‘mixed methods’’ researchers, as if they were part of one of these research communities, rather than talking about their identities in terms of worldviews (John, 2011, p. 33) such as objectivism, constructivism or interpretivism. Moreover, scholars also believe that the benefits of using mixed methods approach allow social sciences research to be examined via different ontological and epistemological lens (Uprichard & Dawney, 2016), in which follow a “practical and outcome-oriented method of inquiry that is based on action and leads” (Johnson & Onwuegbuzie, 2004, p17). In the following parts, the paragraphs will further explain how the quality and characteristic of each approach (i.e., quantitative and qualitative) shape the thesis’s method.

9.10. Methodological Framework

After careful consideration of the ontological and epistemological paradigm. The author has concluded that a mixed methods framework would yield more meaningful results. Other considerations such as industry knowledge, perceived usefulness, knowledge of HR software trends from HR vendors suggest that qualitative research would be able to provide benefit and consolidate the findings with the statistical analyzes. Specifically, within the quantitative methods, a multilevel logistic model is first used to examine the main effect between variables, followed by an analysis of interaction effects. The idea behind this analysis is to find a way to determine if there is an additional effect when the different independent variables are analyzed together rather than individually. (Alfes et al., 2013). To test these hypotheses, this paper carefully selects a list of independent variables and control variables for analysis. Moreover, the qualitative portion of the study also reinforces the idea that a company's financial performance can vary greatly depending on how a company deploys its HR analytics system. In other words, this part of the study highlights the key areas a company needs to pay attention to in order to maximize the chances to gain a competitive advantage (i.e., firm characteristics, challenges, key reasons to adopt HR software, new trends and user traits).

As for the data sources, they come from the ECS dataset produced by Eurofound (2019), which covers more than 20,000 companies across Europe, and includes responses on work practices, HRM, use of skills, competence development strategies and so on. The types of organizational practices that are particularly effective in achieving mutually beneficial outcomes are thereby perfect for evaluating the relationship between variables.

With regard to the qualitative method, semi-structured interviews will be utilized to search for nuance and insightful information (Hennink, et al., 2011). Software vendors are believed to be the most appropriate group to interview because they understand and have the insightful knowledge to answer more advanced questions that would otherwise be perceived as irrelevant to the user community (Hauff et al., 2017; Pudelko & Harzing, 2007). Although the interview questions will be identical, the respondents' perceptions of the questions and their work experiences would often lead to significant differences in their responses, facilitating unanticipated and lucrative lines of questioning beyond the scope of the empirical framework. Online and phone interviews will be chosen specifically to overcome the barrier that most employees were working from home, caused by the peak of the Corona Virus Global Pandemic.

Moreover, software vendors and developers will be targeted through carefully selected LinkedIn and Google platforms. Although these online platforms do not represent the whole population, it is believed that online platforms such as Google and LinkedIn are considered to be the most cost-effective and efficient way to target a specific audience (Vargas et al., 2018). Besides, the data collection for the qualitative part consists of the interview guide, the population of samples, and the design and logical sequence of the interview questions will be developed to ensure reliability and measurement validity (Flower, 2015). The analysis of the interview data will follow both the inductive approach (Yin, 2014a) and the deductive approach (Babbie, 2020), which means that some of the questions from the interview guide will not have predefined codes and will be generated based on the interview data.

In the addition, the validity of the coding process will be monitored carefully. Similarities and differences between individual responses will be compared and evaluated. Finally, the interpretative and aggregate coding will be also considered from the perspective of HRM theories (i.e., SHRM and HPWS) and framework, as this provided a clear picture when analysing. Finally, this study is going to follow the six-step coding principle, a systematic approach that reduces bias and transforms interview transcripts into meaningful results (Ma, 2018; Tesch, 1990).

10.0. Results – Research question three (Main effect)

Although, the benefit of HR analytics has successfully spurred discussion among practitioners and scholars. The findings suggest that across the entire sample there are only about 32% of firms using HR analytics to monitor employee performance. Out of 21,869 companies, 20,047 companies answered this question and 6,499 (32%) companies use HR analytics and 13,548 (68%) companies do not use HR analytics. Of the 6,499 companies using HR analytics, 5,237 (81%) were profitable and 1,262 (19%) either made a loss or only broke even. In contrast, 10,517 (78%) companies that did not use HR analytics were profitable, and 3,031 (22%) either made a loss or only broke even.

Besides, a multilevel logistics regression analysis was also used to examine what factors would influence the firm's financial return. The result table (see appendix 2) presents the estimates for five multilevel logit models where the significant levels are presented by the number of stars (e.g., *p<0.05, **p<0.01, ***p<0.001). The significance level is the probability of rejecting the null hypothesis when it is true. For example, a significance level of 0.01 indicates a 1% risk of concluding that a difference exists when there is no actual difference. Variable pay systems, employees' motivation, the use of HR analytics, change in ownership, frequency in training and payment systems variables are included in all five models with the coefficients of the company size, sector and age being the dummies. However, the five models vary in the inclusion of different macro and micro-level variables.

Model 1 is the simplest model out of the 5 models, containing the three independent variables (i.e., variable pay systems, HR analytics, employee motivation) with control variables (i.e., frequency of training, company size, ownership structure and age). Model 2 includes three additional control variables, namely “frequency of internal hiring” and “turnover rate”. Model 3 builds on the previous model and adds the “autonomy level in job” variable, “employees’ involvement” variable and the “country factor” variable. Model 4 includes all the previous variables but also take into account the “relationship with manager” variable and “firm’s R&D process” model 5 includes all the previous macro and micro variables with one extra control variable, being the “sector” variable.

The results of the analysis (see Table 5, Table 6 and Table 7) showed that organizational practices (i.e., firm-specific practices) such as HR analytics (H2) could be one of the reasons why a better financial return can be achieved for the company. It is believed that companies that use HR analytics achieve higher financial returns because HR analytics improves the ability of managers to support their decisions with facts and data, resulting in better decisions based on evidence and statistical analysis rather than subjective opinions. Companies that use HR analytics to monitor their employees have a positive impact on company financial profit, being (Model 1 = 0.0984, $p < 0.05$), (Model 2 = 0.114, $p < 0.01$), (Model 3 = 0.117, $p < 0.01$), (Model 4 = 0.126, $p < 0.01$), and (Model 5 = 0.116, $p < 0.01$).

Table 5: A summary hypotheses table (Main effect)

Study Three (Main Effects)			
Dependent Variable: Firms' Financial Performance	Accept	Decline	Partially
H1: The higher the motivation of the workforce, the better the firm's financial return is, as higher motivation level strengthens the good behaviour and performance of employees, increasing employee loyalty to create a cohesion force, which contributes to maintaining the stability of the company (DeCenzot et al., 2016; Stone et al., 2020).	✖		
H2: The more complex the HR department an organization has, the more it needs to use HR analytics to monitor employee performance, as HR analytics act as a tool to better manage HR-related matters and ultimately influence a firm's financial performance.	✖		
H3: The higher the proportion of variable pay in a company, the higher the probability that the company will generate a profit, as variable pay converts a portion of the company's fixed costs into variable costs, thereby reducing expenses when performance declines (Robbins et al., 2009).	✖		

As far as employee-specific factors are concerned, the results showed that employee motivation levels and turnover rates play a role. More specifically, the more motivated the employees in the firm, the higher the firm's expected financial return could be, as motivation can serve as a means to reinforce employees' good behaviours and performance, and increase employees' loyalty to create a cohesive force that helps maintain the stability of the company (Stone et al., 2020). In fact, the results of the analysis suggested that the level of employee motivation in companies is an important reason why companies have an advantage over their competitors. One incentive method to encourage employees to be more proactive would be to formulate a set of HR practices that foster a better relationship between employees and the company, and ultimately create a better chance for competitive advantage (Landry, et al., 2017; Paauwe & Farndale, 2017). Specifically, there is support for the hypothesis that motivated employees can improve corporate financial profit (H1). The coefficient for the “very motivated” employees is 0.718, $p < 0.001$ compared to -0.030, $p > 0.05$ for the “not very motivated” employees in Model 3.

With regard to how variable pay systems might influence firms’ financial performance (H3). The results showed that among the four-variable pay systems, pay by “individual performance” and “pay linked to firm performance” were related to firm’s financial performance. Specifically, for individual performance, models 1, 2, and 5 were highly significant, with a p-value less than 0.001, while models 3 and 5 also had a p-value less than 0.01. In other words, the higher the proportion of variable pay that is linked to “individual performance”, the greater the chance that a company will achieve a better financial return. Specifically, the coefficient level for model 1, 2 and 5 are 0.045. And, the coefficient level for model 3 and model 4 are 0.043. In addition, all models for the variable “pay linked to company performance” were found to be highly significant with coefficient level of 0129 for model 1; 0.128 for model 2; 0.127 for model 3; 0.127 for model 4 and 0.125 for model 5. In addition, the results suggested that the variable pay systems do indeed contribute to corporate financial performance, with companies that use one to three types of variable pay achieving higher returns than companies that did not currently use variable pay.

Table 6: Statistical results summary - (Main effect, Research question three)

	Model 1			Model 2			Model 3			Model 4			Model 5		
Statistical results summary	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p
Research question three															

Type of variable payment systems															
Pay by results	-0.004	0.013	> 0.050	-0.004	0.013	> 0.050	-0.004	0.013	> 0.050	-0.005	0.013	> 0.050	-0.012	0.014	> 0.050
Pay by individual performance	0.045***	0.013	0.001	0.045***	0.014	0.001	0.043**	0.014	0.010	0.043**	0.014	0.010	0.045***	0.014	0.001
Pay by team performance	-0.004	0.015	> 0.050	-0.004	0.015	> 0.050	-0.004	0.015	> 0.050	-0.004	0.015	> 0.050	-0.008	0.015	> 0.050
Pay by company performance	0.129***	0.122	0.001	0.128***	0.012	0.001	0.127***	0.123	0.001	0.127***	0.123	0.001	0.125***	0.012	0.001
Number of pay system a company use															
None at all (Ref)															
Single pay system	0.356**	0.119	0.010	0.339**	0.119	0.010	0.339**	0.119	0.010	0.337**	0.119	0.010	0.331**	0.120	0.010
Two pay systems	0.135	0.069	> 0.050	0.139*	0.069	0.050	0.136*	0.069	0.050	0.14*	0.069	0.050	0.147*	0.070	0.050
Three pay systems	0.185**	0.067	0.010	0.197**	0.067	0.010	0.194**	0.067	0.010	0.201**	0.068	0.010	0.201**	0.068	0.010
Four pay systems	-0.001	0.071	> 0.050	0.018	0.072	> 0.050	0.016	0.072	> 0.050	0.028	0.072	> 0.050	0.030	0.073	> 0.050
Use HR analytics to monitor employee performance															
No, HR analytics (Ref)															
Yes, HR analytics	0.098*	0.044	0.050	0.114**	0.044	0.010	0.117**	0.044	0.010	0.126**	0.044	0.010	0.116**	0.045	0.010
Employee's motivation level															
Not at all motivated (Ref)															
Very motivated	0.795***	0.172	0.001	0.722***	0.174	0.001	0.718***	0.174	0.001	0.582**	0.182	0.010	0.611***	0.183	0.001
Fairly motivated	0.521**	0.162	0.010	0.461**	0.164	0.010	0.460**	0.164	0.010	0.370*	0.171	0.050	0.368**	0.172	0.050

Not very motivated	0.003	0.164	> 0.050	-0.030	0.165	> 0.050	-0.030	0.165	> 0.050	-0.042	0.170	> 0.050	-0.046	0.171	> 0.050

Table 7: A summary results table

Hyp	Supported?	Finding
H1	Yes***	Workforce motivation is positively significant to the firm's financial return. It is believed that higher motivation level strengthens the good behaviour and performance of employees.
H2	Yes**	The use of HR analytics is one of the reasons for a firm to gain competitive advantage. It helps monitor employee performance accurately, increase employees loyalty and in return allow firms to achieve better financial return.
H3	Yes**	Companies that use one to three types of variable pay achieving higher returns than companies that did not currently use variable pay.

11.0 Results – Research question three (Interaction effect)

11.0.1. Interaction effect results

The interaction effect analysis was adopted in study three, to assess the potential impact between HR analytics, employee motivation, variable pay systems, and firm financial performance. The hypothesis is that there is a causal relationship between HR analytics, variable pay systems, employee motivation and the financial performance of the company. Specifically, the interaction effects should go beyond the individual main effects of the variables involved. Because HR analytics helps managers consolidate their decisions based on facts and data in employee performance evaluation. If one follows this concept, it would make sense to conclude that HR analytics can help increase the transparency of managers' decisions, increase employee motivation, and ultimately generate a higher financial return for the company. However, based on the result of the analysis, this thesis did not find any significant interaction effects (see Table 8) and therefore, we cannot accept the hypothesis.

Table 8: A summary result table (Interaction effect)

Study Three (Interaction Effects)			
Dependent Variable: Firms' Financial Performance	Accept	Decline	Partially
H4: The interaction effect between HR analytics, variable pay systems, employee motivation and a firm's financial performance is expected to be significant. Specifically, the interaction effects should go beyond the individual main effects of the variables involved (i.e., as HR analytics acts as a tool to provide more accurate variable pay to the employee, indirectly motivating them to perform better).		✖	

In addition, summary tables are provided below. Table 9 shows the results on the *use of HR analytics, employees are motivated and the combination of variable pay.*

Table 9: Statistical results summary - (Interaction effect, Research question three)

	Model 3		
Statistical results summary (Interaction effect)	γ	s.e.	p
Research question three			
Using HR analytics & Employees are motivated (Core) & combination of variable pay			
Core	0.033	0.038	> 0.050
Results based & core	-0.034	0.063	> 0.050
Individual performance based & core	-0.001	0.063	> 0.050
Team performance based & core	0.094	0.093	> 0.050

Company performance based & core	-0.074	0.075	> 0.050
Results based & Team performance based & core	-0.034	0.090	> 0.050
Results based & Company performance based & core	-0.076	0.078	> 0.050
Individual performance based & Team performance based & core	0.103	0.099	> 0.050
Individual performance based & Company performance based & core	-0.084	0.094	> 0.050
Team performance based & Company performance based & core	-0.090	0.109	> 0.050
Results based & Individual performance based & Company performance based & core	-0.086	0.087	> 0.050
Results based & Team performance based & Company performance based & core	-0.110	0.080	> 0.050
Individual performance based & Team performance based & Company performance based & core	-0.074	0.070	> 0.050

Table 10 shows the results on the *use of HR analytics, employees are not motivated and the combination of variable pay.*

Table 10: Statistical results summary - (Interaction effect, Research question three)

	Model 3		
Statistical results summary (Interaction effect)	γ	s.e.	p
Research question three			
Using HR analytics & Employees are not motivated (Core) & combination of variable pay			
Results based & core	0.004	0.075	> 0.050
Individual performance based & core	0.084	0.073	> 0.050
Team performance based & core	-0.062	0.136	> 0.050
Company performance based & core	-0.001	0.099	> 0.050
Results based & Individual performance based & core	-0.039	0.054	> 0.050
Results based & Team performance based & core	-0.150	0.136	> 0.050
Results based & Company performance based & core	0.054	0.105	> 0.050
Individual performance based & Team performance based & core	-0.069	0.111	> 0.050
Individual performance based & Company performance based & core	-0.126	0.110	> 0.050
Team performance based & Company performance based & core	0.189	0.166	> 0.050
Results based & Individual performance based & Team performance based & core	0.019	0.045	> 0.050

Results based & Individual performance based & Company performance based & core	0.033	0.104	> 0.050
Results based & Team performance based & Company performance based & core	0.044	0.157	> 0.050
Individual performance based & Team performance based & Company performance based & core	0.033	0.115	> 0.050
Results based & Individual performance based & Team performance based & Company performance based & core	0.002	0.032	> 0.050

Table 11 shows the results on that companies *do not use of HR analytics, employees are motivated and the combination of variable pay.*

Table 11: Statistical results summary - (Interaction effect, Research question three)

	Model 3		
Statistical results summary (Interaction effect)	γ	s.e.	p
Research question three			
Not using HR analytics & Employees are motivated (Core) & combination of variable pay			
Results based &core	-0.036	0.042	> 0.050
Individual performance based & core	-0.020	0.043	> 0.050
Team performance based & core	0.010	0.072	> 0.050
Company performance based & core	-0.074	0.056	> 0.050
Results based & Individual performance based & core	-0.052	0.044	> 0.050
Results based & Team performance based & core	-0.066	0.091	> 0.050
Results based & Company performance based & core	-0.091	0.077	> 0.050
Individual performance based & Team performance based & core	0.004	0.083	> 0.050
Individual performance based & Company performance based & core	-0.099	0.075	> 0.050
Team performance based & Company performance based & core	-0.138	0.108	> 0.050
Results based & Individual performance based & Team performance based & core	-0.016	0.041	> 0.050
Results based & Individual performance based & Company performance based & core	-0.103	0.091	> 0.050
Results based & Team performance based & Company performance based & core	-0.076	0.082	> 0.050

Individual performance based & Team performance based & Company performance based & core	-0.091	0.075	> 0.050
Results based & Individual performance based & Team performance based & Company performance based & core	-0.033	0.036	> 0.050

Table 12 shows the results on that companies *do not use of HR analytics, employees are not motivated and the combination of variable pay.*

Table 12: Statistical results summary - (Interaction effect, Research question three)

	Model 3		
Statistical results summary (Interaction effect)	γ	s.e.	p
Research question three			
Not using HR analytics & Employees are not motivated (Core) & combination of variable pay			
Results based & Individual performance based & core	-0.098	0.059	> 0.050
Results based & Team performance based & core	0.158	0.118	> 0.050
Results based & Company performance based & core	-0.199	0.108	> 0.050
Individual performance based & Team performance based & core	0.016	0.090	> 0.050
Individual performance based & Company performance based & core	-0.167	0.093	> 0.050
Team performance based & Company performance based & core	-0.071	0.138	> 0.050
Results based & Team performance based & Company performance based & core	-0.206	0.149	> 0.050
Results based & Individual performance based & Team performance based & core	0.000	0.055	> 0.050
Results based & Individual performance based & Company performance based & core	-0.133	0.103	> 0.050
Individual performance based & Team performance based & Company performance based & core	0.035	0.097	> 0.050
Results based & Individual performance based & Team performance based & Company performance based & core	-0.041	0.050	> 0.050

Based on the results of the analysis and the above summary result tables (i.e., model 3), the interaction effect analysis did not find any positive significant relationship between the variables of HR analytics, employee motivation, variable pay systems, and firm financial performance, it means that the presence of one variable does not seem to have a significant positive impact on the relationship between the other two variables.

However, it is important to note that this does not necessarily mean that there is no influence at all. We believe that the relationship between the use of HR analytics, the complexity of variable pay systems, and employees' motivation can be more complicated than the initial thought. For example, the use of HR analytics may be different from other HR practices, and recommendations resulting from HR analytics may not generate the same level of satisfaction among employees, diminishing and undermining the benefits created by HR analytics. Moreover, in a business environment, this may be more difficult to predict the consequences of changing the level of one variable (e.g., towards employee motivation), especially if the use of HR analytics with which employee motivation interacts is difficult to measure or control. As a result, this has the potential to disrupt and influence the interest in HR analytics. Nevertheless, given the statistical power and the high number of cases in the data set, there is reason to believe that the effects of a positive relationship between the three variables are negligible.

Furthermore, based on this finding, it is suggested that organizations cannot simply deploy HR analytics and expect it to improve the overall HR function. There is no guarantee that the organization will gain a competitive advantage. In other words, companies should figure out how best to use HR analytics to fit the environment and industry (e.g., different size, location, trends) in which the company operates (i.e., contingency and configurational theories). Companies should also ensure that the use of HR analytics is compatible with other current HR practices and ultimate business goals.

12.0. Summary of The Quantitative Part

The results for study three revealed that factors such as employee motivation, the use of HR analytics, and variable pay systems (i.e., “pay linked to individual performance” and “pay linked to firm performance”) were found to be critical in determining which factors influence a firm’s financial returns. As for the interaction effects analysis, the results of the analysis revealed no interaction effects in the evaluation of employee motivation levels, the type of variable pay systems, and the use of HR analytics. This interpretation of the statistical models suggests that a company’s financial performance does not depend on the interaction between the independent variables. It is important to note that this does not necessarily mean that there is no influence at all. We believe that the relationship between the use of HR analytics, the variable pay systems, and employees’ motivation can be more complicated than the initial thought. For example, the use of HR analytics may be different from other HR practices, and recommendations resulting from HR analytics may not generate the same level of satisfaction among employees, diminishing and undermining the benefits created by HR analytics. Moreover, in a business environment, this may be more difficult to predict the consequences of changing the level of one variable (e.g., towards employee motivation), especially if the use of HR analytics with which employee motivation interacts is difficult to measure or control. As a result, this has the potential to disrupt and influence the interest in HR analytics. Nevertheless, given the statistical power and the high number of cases in the data set, there is reason to believe that the effects of a positive relationship between the three variables are negligible.

In the following sections, the qualitative part of the study aims to reinforce and provide a comprehensive understanding of why and how a company's financial performance can be highly dependent on a company's ability to deploys its HR analytics system. In other words, it aims to highlights some of the key areas a company needs to pay special attention to in order to maximize the chances of gaining a competitive advantage (i.e., firm characteristics, challenges, key reasons to adopt HR software, new trends and user traits).

13.0. Qualitative analysis

The purpose of this section is to better understand the connections or contradictions between qualitative and quantitative data. This allows researchers to explore different perspectives and uncover relationships that exist between the complex layers of the multi-layered research questions and facilitates different ways to enrich the evidence so that questions can be answered more thoroughly (Wisdom & Creswell, 2013).

Both quantitative and qualitative data were collected and analysed as part of this research. For example, an ECS survey was used to collect information on the use of HR analytics and relevant topics. These data were then analysed using statistical techniques such as descriptive statistics and logistic regression analysis. In addition, in-depth interviews were conducted with individuals (e.g., software developers) to capture their perspectives and experiences on the same topic.

It is important to note that the link between quantitative and qualitative research is that they are mutually reinforcing. Quantitative data can provide a broad overview of how HR analytics influence an organization's operation and can be used to identify patterns, trends, and relationships. However, they cannot have the depth and richness of qualitative data. Qualitative data, on the other hand, can provide a deeper understanding of the topic by capturing context, understanding of individual experiences, and nuances of a phenomenon. However, they may not be as generalizable as quantitative data. Together, these two types of data can provide a comprehensive understanding of a topic that would not be possible with just one method alone.

In summary, this research was conducted through a combination of quantitative and qualitative methods, collecting and analysing both types of data. Using both methods together can provide a more comprehensive understanding of the use of HR analytics than would be possible with just one method alone, with each method providing unique insights and a better understanding of a topic. Both types of data can be used together to increase the validity and reliability of the research (Burns, 2000; Vanhala & Kolehmainen, 2006).

This section will begin by presenting the target population, research method, interview guide, and interview results. Contributions in this context include a more nuanced understanding of the role of HR analytics and HR artificial intelligence in organizations. In addition, it is important to clarify that since this is an exploratory study, its purpose is not to provide a final and definitive answer to the field of HRM. Rather, it aims to construct existing journals, provide a broader understanding of the subject, and form the basic concepts for future discussions.

Based on the research question, a semi-structured interview approach was chosen in this thesis, which aims to obtain information through conversational communication. This approach is considered to be the most appropriate option, as it provides the right balance between structure questions and knowledge sharing (i.e., respondents can talk about their own knowledge and experiences related to the topic) (Arksey & Knight, 1999; Bamberger, 2000). Specifically, questions were developed based on literature (e.g., Angrave et al., 2016; Aral et al., 2012; Edwards et al., 2019; Huselid, 2018; Kryscynski et al., 2018; Marler and Boudreau, 2017; Patre 2016; Schiemann et al., 2018; Van den Heuvel and Bondarouk, 2017) and business reports (e.g., Bughin et al., 2017; Collins et al., 2017; KPMG 2013; Kukde, 2016; PwC, 2020).

13.1. Target population

With regard to the target group, special care was taken to ensure that all interviewees in this study were familiar with HR analytics and/or HR artificial intelligence, as the interview guide (i.e., interview questions) required in-depth knowledge and experience on this topic (Hauff et al., 2017; Pudelko & Harzing, 2007) (Hauff et al., 2017; Pudelko & Harzing, 2007). Moreover, all software providers were targeted through carefully selection via LinkedIn and Google platforms. Although these online platforms do not represent the entire population, it is assumed that online platforms such as Google and LinkedIn are the most cost-effective and efficient way to target a specific audience (Vargas et al., 2018). Ultimately, forty-two companies were contacted for this research. However, only eleven companies participated in this qualitative sample. This reflects the relative difficulty of getting software providers to participate during a nationwide pandemic lockdown.

14.0. Method

In scientific research, no method is perfect, and each method has its own strengths and weaknesses. In qualitative research, there are a variety of data collection methods that can be applied, including participant observation, focus groups, interviews, discourse analysis, and documentary analysis (Bell et al., 2018; O'Cathain, 2018), but the most commonly used methods, especially in

HRM research, are interviews and focus groups. Due to the nature of the research questions, this section will focus primarily on the interview method rather than the other methods described above.

The interview method is considered the most appropriate option for collecting reliable primary data because it allows the author to collect data on a given topic using the same methods and under the same circumstances (King & Horrocks, 2010). Researchers have also suggested that the interview method reflects a view of social science knowledge that is preliminary, inconsistent, complex, and contextualized (Arksey & Knight, 1999). In particular, it can be used to assess the relationship between different aspects, consolidate a better understanding of the situation, and provide the author with details of behavioural, emotional, and personal opinions that quantitative research cannot provide. However, it is also important to note that qualitative research is often subjective, which means that generalizing from a broader context can be more difficult and the objectivity of findings is often limited (Bamberger, 2000).

There are three types of interview structures, namely the structured interview, the unstructured interview, and the semi-structured interview. The structured interview is an interview method that involves a high degree of control during the interview process (Bamberger, 2000). The goals and flow of the interview must be structured according to the criteria of the interview topic. For example, the number of questions, the order in which they are asked, the time allotted to each question, and the manner in which responses are recorded are completely standardized. To ensure this uniformity, most interviews are conducted using predesigned questionnaires. The main advantage of a structured interview is that the results are easily quantified and can be statistically analysed (Townsend et al., 2016).

If this paper were to conduct from structured interviews, a possible benefit would be that the author would be able to create a standardized list of questions related to HR analytics and HR artificial intelligence prior to the interview. This would also mean that the interview process would be more objective and the author would be able to make a fair comparison of the software vendors' answers and understand what makes HR Analytics and HR artificial intelligence stand out from other traditional HR software. However, the downside of structured interviews is that the author will not be able to gather additional knowledge beyond the predesigned questions, thus reducing the opportunity to generate new insights that are important in the discovery phase of HR analytics and HR artificial intelligence.

Compared to structured interviews, unstructured interviews are very flexible and do not have any predesigned interview questions, forms, and standardized procedures for gathering information. Respondents are free to talk about their own opinions and feelings about the events surrounding the topic. In other words, in this type of unstructured interview, the order of questions asked and the way respondents answer are not consistent. Therefore, questions must be developed spontaneously during the interview. Researchers believed that unstructured interviews often generate many new ideas and concepts that interviewers did not expect, providing great insight into new research areas (Bamberger, 2000; Townsend et al., 2016). However, because the information from the interviews is difficult to evaluate quantitatively, the results of interviews tend to depend on the quality, experience, and skills of the interviewer (Townsend et al., 2016).

If unstructured interviews were used in this work, the possible advantage would be that the author would have the opportunity to gain new insights, which is important in the exploration phase of HR Analytics and HR artificial intelligence. The software vendors could set their own priorities and have an in-depth and free-form conversation about a very specific area of HR analytics (e.g., questions focused only on descriptive analytics) and HR artificial intelligence (e.g., questions focused only on NLP), which would help the researcher develop a true sense of the software vendors' understanding of HR software. The drawback, however, is that it is extremely difficult to get a concrete answer in the HR domain in an unstructured interview. Since there are no pre-coded responses in unstructured interviews, the qualitative data from unstructured interviews are difficult to analyze and categorize. In other words, the research guide and instrument therefore cannot be replicated by other researchers, which reduces reliability.

Last but not least, the semi-structured interview is a type of interview method that falls between structured and unstructured interviews, where the interviewer needs to design the outline of the interview process based on the research hypotheses. Although the interview questions would be identical, the respondents' perceptions of the questions and their work experiences would often lead to significant differences in their responses (Arksey & Knight, 1999; Bamberger, 2000).

Semi-structured interviews were used in this thesis. The benefit was that the author was able to generate new insights from a series of predefined, open-ended questions related to HR analytics and HR artificial intelligence. Software vendors had the opportunity to talk in-depth about their own experiences that are closely related to the questions in this thesis (e.g., what are the issues/ challenges that users face when they start using HR analytics and HR artificial intelligence software products?) Reliability and validity were also critical factors of why this thesis adopted the semi-structured interview method, as the author believes this would be the best way to make a fair comparison of software vendors' answers regarding HR analytics and HR artificial intelligence. Moreover, the author was also aware that semi-structured interviews may also interfere with the ability to gather additional knowledge beyond the given topics, reducing the possibility of gaining new insights, which is important in an exploratory study of HR analytics and artificial intelligence in HR. Nonetheless, after reviewing the advantages and disadvantages of the various interview methods described above, the semi-structured interview method was deemed the most appropriate choice for the research questions.

14.1. Inductive and deductive approaches

Having decided which interview method to use in this thesis. It is now time to examine how the interview guide and interview transcripts were developed and analysed from the perspective of the inductive and deductive approaches. In the deductive approach, a hypothesis (or multiple hypotheses) is formulated based on existing knowledge and information, and then an interview guide is designed. (Wilson, 2014). It is important to note that the term “deductive” means “reasoning from the particular to the general. If a causal relationship or link seems to be implied by a particular theory or case example, it might be true in many cases” (Gulati, 2009, p.42). In the case of the inductive approach, it focuses on identifying patterns through data collection and presenting theories and knowledge in the final stage of the research process. In other words, it aims to explore and develop a new theory where it moves from specific observations to broader generalizations and concepts. (Gratton and Jones, 2009). However, it is important to emphasize that the inductive approach does not imply disregarding theories when formulating research questions and objectives. Researchers should never view the inductive approach as an element that prevents them from using existing theories to formulate ideas (Saunders et al., 2009; Strass and Corbin, 1990).

By following these two approaches, the deductive approach was adopted in this thesis to assist the author in developing the interview guide using existing knowledge and information (e.g., HR analytics enable organizations to consolidate decisions via facts, data and reason). Specifically, questions were developed based on literature (e.g., Angrave et al., 2016; Aral et al., 2012; Edwards et al., 2019; Huselid, 2018; Kryscynski et al., 2018; Marler and Boudreau, 2017; Patre 2016; Schiemann et al., 2018; Van den Heuvel and Bondarouk, 2017) and business reports (e.g., Bughin et al., 2017; Collins et al., 2017; KPMG 2013; Kukde, 2016; PwC, 2020). The inductive approach, on the other hand, follows the idea of grounded theory procedures to help develop more knowledge and theory surrounding HR analytics and HR artificial intelligence.

14.2. Validity and reliability

A good qualitative study can help us understand an otherwise enigmatic or confusing situation (Eisner, 1991), but a very common criticism of the qualitative research approach is that it provides little evidence of scientific generalization, which may compromise its validity (Burns, 2000; Vanhala & Kolehmainen, 2006). Therefore, researchers suggest that a well-designed qualitative study should cover construct validity, internal validity, external validity, and reliability.

To ensure the validity of this study, this thesis considered structural validity, internal validity, external validity, and reliability perspectives as a whole. In terms of structural validity, this thesis relied on multiple sources of evidence during the data collection phase to promote convergent lines of inquiry, which further strengthened data analysis and construct validity (Whitworth & De Moor, 2009;

Yin, 2003). For example, Healy and Perry (2000) and Yin (2003) suggested that researchers should merge their findings with theory to improve study validity. Therefore, in this thesis, the author ensured that a list of high-quality references was included in the coding process to support the theoretical connections.

For internal validity, the thesis should usually establish a causal relationship between variables. The goal here is to rule out alternative explanations for each outcome, where the observed results should represent the truth in the population and not any other possibility. However, it is important to note that Ma (2018) and Yin (2014c) have pointed out that this may not necessarily be the case in exploratory studies (i.e., HR analytics and HR artificial intelligence) due to the lack of sample size and theoretical support. Similarly, external validity refers to the extent to which findings can be generalized to other contexts. This study attempted to do so by combining HRM theories and interview questions with the quantitative chapter to generalize specific findings.

In terms of overall reliability, it refers to the consistency of a measure and whether the results can be reproduced under the same conditions (Singh, 2022). This thesis, not only this chapter, but the entire process from the beginning of the introductory chapter to the end of the concluding chapter was documented with traceable references. For example, the interview guide was developed based on literature (e.g., Angrave et al., 2016; Aral et al., 2012; Edwards et al., 2019; Huselid, 2018; Kryscynski et al., 2018; Marler and Boudreau, 2017; Patre 2016; Schiemann et al., 2018; Van den Heuvel and Bondarouk, 2017) and business reports (e.g., Bughin et al., 2017; Collins et al., 2017; KPMG 2013; Kukde, 2016; PwC, 2020). While, the coding process was followed the six-step principle of coding to obtain meaningful insights from the interview transcripts (Ma, 2018; Tesch, 1990; Yin, 2014a). A summary table of contents was developed to capture the categories of codes, concepts, and theories to demonstrate the repeatability of this research (see table 13).

Table 13: A summary of the validity

Test	Description	Research tactics	Phase of research
Construct validity	Establishing correct operational measures, the extent to which the measurements used, actually test the hypothesis or theory they are measuring	• Use of multiple sources of evidence • Establish a chain of evidence • Data collection from multiple sources	Data collection – primary and secondary data from websites and interviews
Internal validity	Establishing causal-and-effect relationships as distinguished and eliminate alternative explanations for a finding, in which the observed results represent the truth in the population and no way else	• Sample selection for information richness • Explanation building with published journals	Research design – tried to arrange as many interviews as possible during Covid outbreak.
External validity	External validity is the extent to which the results can be generalized to other contexts	• Sample selection for theoretical replication	Research design
Reliability as a whole	Demonstrating that the operations of study can be repeated with same results	• Interview guide developed for the collection of data	Research design – developed an interview guide for the interview

14.3. Reflexivity

Last but not least, it is also important to consider and reflect on the paths and decisions made during the doctoral research process. Researchers believe that this process on critical reflection provides both readers and authors with a deeper understanding of how the research process shapes its outcome (Guillemin & Gillam, 2004). This thesis was conducted by a doctoral student who has studied the topic in-depth and has practical experience as a business professional. However, the author has limited experience in conducting qualitative research. Therefore, most of the knowledge used to develop this research framework came from textbooks and research papers. Although this was useful in building a knowledge base, most of the decisions in these chapters were made according to the judgment of the author, who followed the recommendations of his supervisors. The knowledge underlying these decisions was realistic and was selected based on the method that was most appropriate for the research questions stated above. In addition, the author was aware that some data could be subjective and may not provide a complete picture of HR analytics and HR artificial intelligence applications, but detailed reasons and references were provided for each decision to overcome this common concern with HRM (Pudelko & Harzing, 2007). Therefore, readers should feel confident in reading the paper as the results of this work have been compiled from multiple sources with academic references and are written at a high level of quality.

14.4. Interview guide

This section will first discuss a description of the interview guide design, as well as the reason why these questions have been selected (see table 12). Researchers suggested that although an interview method has been chosen, it is still necessary to create an interview guide as a memory aid to ensure that the quality of the interview can be properly implemented (Hennink, et al., 2011). The purpose of an interview guide is to provide an interviewer with a systematic way to ensure that responses are consistent across participants (Arthur et al., 2014).

This interview guide begins with questions related to the participants' background, especially about their role, responsibilities, and experience in the company. The aim here was to create a relaxed and casual atmosphere between the interviewer and the interviewee (Affleck & Alexandre, 2020). Following this, the interview guide moves on to questions that focus on the companies' software, questions such as software features and challenges were included to shed light on why the adoption rate of HR analytics and HR artificial intelligence is lower than expected, despite evidence that HR software is paying off in businesses (Dahlbom et al., 2019; Guenole et al., 2017; Kryscynski et al., 2018; Levenson, 2011). Questions about the HR software industry were included to examine industry trends. A final question was also added at the end to allow participants to reflect on the interview and share information that they had not been asked earlier in the interview (Braun & Clarke, 2013).

Furthermore, the interview guide was also designed based on the review from the previous chapter about HR analytics and HR artificial intelligence. Specifically, the questions followed various researchers' interests and recommendations (Aral et al., 2012; Kryscynski et al., 2018; Marler and Boudreau, 2017; Schiemann et al., 2018; Van den Heuvel and Bondarouk, 2017). Besides, the results of the quantitative study also provide a solid basis for designing the questions. For example, the results of study two showed that company-specific factors are most important in explaining why companies do or do not use HR analytics to monitor employee performance, thus supporting the hypothesis that larger companies have the structural and managerial capabilities to leverage the potential of HR analytics. Therefore, the interview guide attempted to test this hypothesis by asking the following question: "Who are your customers, are they small/ large companies, which industries did they belong to, are they domestic/ multinational companies, other criteria?"

In addition, all of the above recommendations and developments were implemented based on the criteria presented in the study by Hennink et al. (2011). A summary table of how the interview guide was developed is listed below in table 14.

Table 14: A summary table of how the interview guide developed
• Ensure the interviewees understand the questions.
• Ensure the concepts, sentences and words are adapted to the context of the interviewees.

• Some questions might need to be rephrased to fit with the target groups.
• Ensure the order of the questions is logical for the interviewees.
• Ensure the research questions can be answered with the information that is gathered.
• Ensure the duration of the interview is not too long or too short.
• Ensure to include introduction questions that focus on the interviewees' background and demographic information. This provides a relaxed atmosphere for the interviewees.
• Understand that knowledge questions (e.g., product features and usefulness of software) are related to what participants think. It is based on their experience rather than anything that is necessarily true.
• Ensure all questions are related to the HR software industry. It should be something that cannot be easily obtained from secondary sources. The aim is to establish and understand what the respondent thinks about the topic and how their thoughts relate to their values.
• The interviewer should include follow up questions when necessary. Getting the interviewees to elaborate their answers and allows the interviewer to gain a deeper understanding and insight into the interviewees' answers
• Ensure the tenses are correct in the questions. Because this might affect interviewees' responses.

All interview questions were open-ended so that the interviewer could explore why and how a particular situation occurs. Notably, the word "why" was modified to "how" during the interview as Yin (2014d) suggested that this would create a friendly, non-threatening atmosphere that would encourage interviewees to share their opinions and improve the viability of the content for reference. In addition, interviewees were reminded prior to the interview that they should focus only on the most important HR analytics and HR artificial intelligence applications that contribute to the company's economic success, as some companies may have multiple HR analytics and artificial intelligence applications (Hauff et al., 2017). All interviews were conducted in English and lasted between 45 and 55 minutes.

14.5. Interview group

A list of respondents working in HR analytics and/ or HR artificial intelligence was contacted via email or direct message on LinkedIn. The respondents were either managers, directors, or employees that are knowledgeable about the product. A total of eleven respondents were interviewed, (interviewees 6 and 7 are working in the same organization), one of which was an email questionnaire, and their profiles are summarized in table 15:

Table 15: A summary of the interviewees

Interviewee	Job position	Background	Company experience (month)	HR analytics (H)/ Artificial intelligence (A)	Gender
1	Sale development representative	Education, sale and marketing	18	H & A	F
2	Business partner	HRM	24	H & A	F
3	Product manager	Marketing	12	H & A	M
4	Director	IT and software	6	A	M
5	Director	Software engineer and HRM	12	H & A	M
6	Data scientist	Data specialist	9	H & A	F
7	Researcher & HR manager	HRM	42	H & A	F
8	Customer success	Teaching and sale	18	H & A	F

	manager				
9	Product consultant	Analytics and programming	36	H & A	M
10	Client success manager	Recruitment software	12	H & A	F
11	Business development associate	Business	38	H & A	M
12	CEO	Software engineer	34	H & A	M

Due to the nature of the respondents' jobs, they have extensive knowledge of HR-related software such as HR analytics and/ or HR artificial intelligence. The sample size is mixed with different gender, position and age to cover a broader picture of the industry. In addition, all interviews were conducted between 2019 and 2021, and it was acknowledged that some potential bias could arise from the fact that the respondents were software vendors selling services to customers. Some respondents may have been concerned that unfavourable opinions would impact their company's reputation, image, and performance, and therefore may not have answered some questions truthfully. To minimize this bias, each respondent was reminded prior to the interview that any information would not be shared and would be kept strictly confidential.

14.6. Transcription

The discussion of quality transcription in qualitative research has always been the spotlight in the academic community (Hagens et al., 2009; MacLean et al., 2004; Roller, 2019). Transcription is the process of converting recorded material (i.e., spoken words) into a written format (i.e., text) and, as such, is usually with the two types of transcription format: A full (verbatim) transcription approach and a partial (non-verbatim) transcription approach.

For the verbatim transcription approach, it refers to the process of converting every second of every interview word for word. It is a method that requires a much more detailed level of transcription than its counterpart. Researchers suggested that this approach would tend to apply in discourse analysis, verbal screening practices and conversation analysis, where the author is looking to evaluate how the respondents speak and the language that they use in different scenarios (Barkhuizen et al., 2013; Powers, 2005). For instance, an interviewer might want to use the verbatim transcription approach to evaluate the notation from sentences, how often a respondent pauses in a sentence, what kind of voice intonations and emotions does the respondant show. On the other hand, the non-verbatim is much more common and reader-friendly to understand (Rajagopal, 2015), as it focuses on transcribing the interview conversation into a clean text, especially in highlighting the key points and the main theme of the topic, but eliminating the repetitions that occur during the respondents' speech patterns (King & Horrocks, 2010; Rajagopal, 2015). After carefully considering the strengths and weaknesses of both methods, the non-verbatim approach was chosen.

15.0. Data analysis

The purpose of this section is to provide readers with knowledge of how the data was analysed since the topic is in an exploratory phase and data were collected in semi-structured interviews.

The analysis of the interview data followed both the inductive approach (Yin, 2014a) and the deductive approach (Babbie, 2020), which means that some of the questions from the interview guide do not have predefined codes and were created based on the interview data. For example, one of the questions looks at the “awareness of products”, which has not been discussed in other literature. The idea behind this is to develop and gather new knowledge from a single data collection procedure. Therefore, when formulating a new theory, it is important to follow the ground theory approach, which includes the “descriptive phase”, the “interpretive phase”, and the “overarching phase” (Strass and Corbin, 1990).

15.1. Data procedures

For the descriptive phase, it includes generating categories of information in which data should break down into discrete parts, closely examine its validity, and compared for similarities and differences. The main objective is to identify information that might be helpful in answering the research questions, rather than trying to interpret its meaning. The interpretation phase is about bringing the discrete and separate pieces from the previous phase back together to make connections between categories, which allows researchers to bring the complexity of the context into closer context, using only the most relevant and noteworthy information. In other words, this step goes beyond describing the relevant features of the participants' interviews and focuses more on interpreting what people say. Last but not least is the overarching phase, which involves the process of creating a core category and relating it with other sub-categories (Mertens, 2014). Researchers suggested that at this stage, although the coding level is very similar to the interpretive phase, it is done at a much higher and more abstract level of analysis (Strass & Corbin, 1990) where all categories should be identified and linked with theories and frameworks.

Following the idea above, this study followed the six-step principle of coding to obtain meaningful insights from the interview transcripts (Ma, 2018; Tesch, 1990; Yin, 2014a).

- Step one: Read all interview transcripts, get an overview of the information, and think about the general meaning of the research questions.
- Step two: choose one interview transcript as a starting point, go through each question and make notes in the margin, abbreviate some descriptive terms as codes, and begin to develop concepts based on these codes.
- Step three: continue the coding process for the remaining interview

transcripts and divide them into different categories based on different concepts. At this stage, a few interview transcripts could be linked to specific references to enhance their validity (Yin, 2014a).

- Step four: review previous interview transcripts and reassign cluster categories and assess whether new categories or codes should be created (Ma, 2018).
- Step five: Shorten categories by grouping similar categories together. Ensure that the codes are now next to the appropriate sections of text. It is important here to create a coherent picture of how each category can fit together (Ma, 2018; Pratt et al., 2006).
- In step six, select the final codes and finally develop a content summary to provide meaningful results (Creswell & Creswell, 2009a).

In table 16, it provides relevant examples of how this thesis combines interview transcription with open codes.

Table 16: Example of Open Code

Interviewee	**Transcription**	**Open codes**
2	HR professionals... are not comfortable with tables, graphs, charts and numbers. Sometimes, the software provides the suggestions but they (customers) may not be able to implement them due to a lack of understanding of tables, graphs, charts and numbers.	Analytical skill
4	It is difficult for users to get the most out of our software. Companies tend to use our software for a specific purpose. But in reality, our software would be able to handle many tasks. Yes, this could be the case for some (tasks) but if you have enough information from the database… our software would be able to handle it.	Data collection, training and development
6	The anonymous survey question …some employees	Trust

	have doubts about the anonymity of the tool because… they are working in a small team group of 5 to 10 people…they are scared manager/ peers can figure out if they arise a concern.	
6	Some employees are not willing to use the software. Because they are worried, they might lose their jobs... Some managers are doubtful about the software explanations.	Training and development
8	A lot of the employees lack understanding and knowledge in data... The second aspect is about how to use our software correctly. For example, if the business problem is very complex, then the client also needs to ensure they have the skill to carry out the analysis.	Analytical skill, training and development

In table 17, it provides relevant examples of how open codes are linked with different concepts.

Table 17: Codes to Concepts example

Codes	**Concepts**
Analytical skill	The ability to understand descriptive, visual and statistical methods to interpret people data and HR processes.
Data collection	Data collection is the single most important step in solving any analytics and AI problem.
Training and development	It is an educational activity carried out to improve the employees' knowledge and skills, provide information and guidance on how to perform better.
Trust	Trust can be defined as 'an individual's expectation that some organised system will act with predictability or goodwill' (Maguire & Phillips, 2008) which ultimately affects productivity, turnover and business culture.

Through comparative analysis across all of the interview transcripts, we succeeded in classifying concepts into different categories that are relevant to the research question of the paper. An example is outlined in table 16 below:

Table 18: Concepts classification

Concepts	**Category**	**Theoretical link**
The ability to understand descriptive, visual	Challenge	HPWS

and statistical methods to interpret people data and HR processes.		
Data collection is the single most important step in solving any analytics and AI problem.	Challenge	HPWS
It is educational activities carried out to improve the employees' knowledge and skills, provide information and guidance on how to perform better.	Challenge	HPWS
Trust can be defined as 'an individual's expectation that some organised system will act with predictability or goodwill' (Maguire & Phillips, 2008) which ultimately affect productivity, turnover and business culture.	Challenge	HPWS & Trust

The key idea of the above tables (see tables 16, 17 and 18) outlines the importance of the coding process and refinement process of how to elaborate a relationship with theoretical evidence (Strass & Corbin, 1990).

Overall, this thesis translates *interview transcripts* into *codes*, then *concepts*, and then *categories*, and finally links them to *theoretical frameworks*. The example outlined below in table 19 illustrates how the author refines the interview transcripts to each stage.

Table 19: Example of linking interview transcripts to theories and concepts
An Interviewee Statement: "*HR professionals... are not comfortable with tables, graphs, charts and numbers. Sometimes, the software provides the suggestions but they* (customers) *may not be able to implement it due to a lack of understanding in tables, graphs, charts and numbers*".
Step 1: By evaluating and comparing this statement with other interview transcripts, the author labelled it as "analytical skill" under "open code".
Step 2: Once the "open code" has been identified, the author translates it as a "concept". (i.e., "the ability to understand descriptive, visual and statistical methods to interpret people data and HR processes").
Step 3: The author linked the concept to a theory. Under this scenario, the author believes the interview statement should be linked with HPWS and AMO theory. Because it is reasonable to assume that simply providing opportunity and implementing HR analytics alone will not necessarily benefit the organization. Instead, organizations should solve this "challenge" by focusing on employees' ability and their

motivation.

15.2. Interview findings and discussion

For the qualitative findings, the study provides additional support for five specific areas, namely *firm characteristics, challenges, key reasons to adopt HR softwar*e, *new trends and user traits* in the field of HR analytics and HR artificial intelligence.

Regarding firm characteristics, all interviewees seem to agree that there is no particular size or industry that would be more likely to adopt HR analytics and HR artificial intelligence. It is believed that different software functions are needed for different stages of the business, that is in the growth, maturity and decline stages (Baird & Meshoulam, 1998). Therefore, the purpose of adopting HR analytics and HR artificial intelligence might be adjusted depending on the stage of development of the organization. As the organization grows and evolves, different HR analytics and HR artificial intelligence functions would be implemented to achieve different goals. This idea was also supported by Greiner (1998) and Dooney (2015), where researchers suggested that "a company's problems and solutions tend to change markedly as the number of employees increase" (Greiner, 1998, p.4), so managers could expect different problems depending on the cycle of the business. However, it is also important to point out that interviewee (4) mentioned that: (although) *I haven't seen a major difference* (between company size and industry) *…but I would say that a bigger and flatter management style organizations are more open to technology* (i.e., HR analytics and HR artificial intelligence). By looking at this statement and the theory of economies of scale, it is reasonable to assume that as the number of employees increases, it will be more advantageous for the company to utilize the relevant HR technology because the cost per unit of output decreases as the size of the company's operations increases. In addition, HR analytics must be embedded in an environment with structure, policy and management capabilities. This means companies not only need to have the knowledge and capability to leverage existing data, but they also need to have the right regulations in place for managers to collect, store and analyse it (Angrave et al., 2016; Stone & Lukaszewski, 2009; Vargas et al., 2018).

Focusing directly upon the challenges of the use of HR analytics to carry out HRM functions, the results demonstrated that many clients of the interviewees lack the relevant knowledge to understand and implement data analysis. The reason being, historically, HRM positions did not normally require an individual to have strong analytical skills and mathematical ability to carry out HRM functions (Roberts, 2009; Ulrich & Dulebohn, 2015). If HR professionals would like to make real contributions to SHRM, their analytical ability needs to be improved as researchers proposed that HR professionals' analytical skills might be considered as one of the most critical elements in HR analytics adoption (Lawler, 2006; Roberts, 2007). For example, interviewee (9) suggested that: *the user should have some level of analytical skills and should have great knowledge about the department. For example, people who know the data within the HR department would have a higher chance to ask the 'right' questions.* In addition, interviewees (6 and 7) also mentioned another challenge and said: *some employees are not* *willing to use the software. Because they are scared, they might lose their jobs.* This behaviour could be associated with technology avoidance based on the idea of “Technology Avoidance Threat Theory” (TATT) (Liang & Xue, 2009) where an employee’s motivation is to invoke a safeguarding mechanism against its use.

As for the main reasons why certain companies chose to use HR analytics and HR artificial intelligence, while others did not, the interview results suggest that: Firstly, HR analytics and HR artificial intelligence software enable managers to track and evaluate employees’ performance in a new way that was previously unavailable (e.g., select a high-performance individual from a group). Interviewees (6 and 7) also suggested that SMEs typically adopt HR-related software to achieve higher levels of engagement and focus primarily on reducing costs, while larger companies aim to use HR analytics and HR artificial intelligence to gain a larger market share and improve the accuracy of performance tracking. Besides, interviewee (4) also said: *they* (the clients) *would like to use* (HR analytics and HR artificial intelligence as a way) *to reduce cost, improve business efficiency and solve their business problems… create a positive relationship with the employees… maintain a good retention rate, yet gain a better profit return.* Moreover, interviewee (11) and interviewee (12) also proposed that as HR managers become too busy to handle standardizing tasks, HR analytics and HR artificial intelligence can act as a point-of-contact between employees to free up some more time for HR managers to deal with other HR problems. Therefore, by looking at the interview results, it is suggested that when a firm’s HR practices become more sophisticated and complex, they appear to be a key reason to adopt HR analytics and HR artificial intelligence. This finding was supported by the H2 from the quantitative analysis that the degree of complexity in the firm process is a strong motivator for firms to gain an advantage over competitors and make use of HR analytics to monitor the performance of employees.

As for the trend in the HR software industry, most respondents agreed that the next trend in HR analytics and HR artificial intelligence will be primarily focused on automated processes for handling organizational tasks. Specifically, interviewee (4) suggested that they are expecting to see more advanced artificial intelligence to carry a three-way conversation with managers. For instance, if two managers are discussing and deciding which training program is best for a group of employees on an online platform, an artificial intelligence assistant could step in and make suggestions while also making reservations for the employees simultaneously.

In addition, most of the interviewees do not know any services and/ or products that are available but not in use because of the lack of acceptance. However, interviewee (4) suggested that facial recognition may not be accepted now in society as *facial recognition is not fully developed within the industry (from the) data protection policy (perspective)… different countries might have different policies… so companies are worried that the (initial) R&D cost might not be able to recover from the product… if (one day) a country(ies) changes their policy we* *(the company) might lose all of our capital spendings… and a lot of privacy issues, people do not want their faces to be recognised and to be tracked.*

16.0. Four fundamental qualities

As organizations increasingly adopt a data-driven approach to work, the ability of HR managers to influence in an environment where decisions are made based on big data and technology becomes increasingly important. Due to the vast amount of information available, the ability to use this data to make collective decisions to achieve goals is a critical factor for successful managers and organizations. Based on the results of the interviews and literature review, the below section is going to illustrate four fundamental qualities that are essential for HR analytics users (e.g. HR managers), being realization, collaboration, analytics and influence skills.

16.0.1. Realization

With the ever-increasing amount of data and information, analytically-minded HR managers need to closely monitor their environment and identify which data could be beneficial to the business. In this context, HR managers should not fall into the trap of perception blindness, as this often happens when large amounts of data and information are present at the same time. In addition, managers should not expect a particular outcome based on past events and therefore disregard the results. By being aware of this possibility, HR managers can remain open to important information in the data that might otherwise be overlooked. (Angrave et al., 2016; Huselid & Jackson, 1997; Stone & Lukaszewski, 2009; Thompson & Heron, 2005; Vargas et al., 2018; Levenson, 2011). Managers need to be conscious of the type of data they are collecting, as data is often unreliable.

In addition, HR managers need to ensure that the value of implementing HR analytics should be closely related to the business and its strategy, rather than addressing issues that seem relevant only from a research perspective (Ellmer and Reichel, 2021).

16.0.2. Collaboration & data sharing

Building on the perspectives suggested above, HR managers should also encourage information sharing and collaboration among team members and other departments to ensure that the results of the analysis are used in a meaningful way. Information sharing ensures that a variety of individuals and team members have access to multiple sources of information to generate appropriate knowledge for decision making. HR managers should also foster psychological safety, where individuals feel free to express their opinions and share unique information that they may not otherwise consider relevant. Moreover, researchers also found out that the reluctance in information sharing between departments (Angrave et al., 2016; Dijk & Rothweilwe, 2016) also prevent managers from making use of HR analytics. Departments tend to collect data that is beneficial for their own need without considering too much about others. Because not all data would be stored in a single location. Therefore, if managers would like to consolidate a decision, it is advised that combining data collected from multiple sources would create greater efficiency and accuracy in decision making (Diez et al., 2019).

16.0.3. Analytical and theoretical skills

HR analytics requires HR managers to have certain specific skills such as problem-solving, data analysis, and pattern recognition (Angrave et al.2016; Kryscynski et al. 2017). However, these skills are in short supply. The reason for this is that in the past, HRM positions did not normally require an individual to have strong analytical skills and mathematical ability to carry out HRM functions (Roberts, 2009; Ulrich & Dulebohn, 2015). Besides, HR managers should also have knowledge in research and theoretical knowledge related to HRM to build on the question related to a specific topic, as researchers suggested that internal knowledge of the HR analytics team is an important element that helps capture the information needs of decision-makers and to extend their knowledge on a particular issue (Ellmer and Reichel, 2021). Therefore, hiring or working with individuals who do not have relevant experience or knowledge can lead to misinterpretation or misspecification of the analytics results.

16.0.4. Influence

Influencing is at the heart of management and is especially necessary for HR managers. Given the many alternative options employees can use instead of HR analytics, HR managers must be able to convince others of the benefits of using HR analytics to achieve the desired outcomes and goals. For example, by modifying a particular analytic result and tailoring it to a specific situation. Or, demonstrating how HR analytics results can have a financial impact on the organization are all good examples of drawing attention to the benefits of HR analytics (Ellmer and Reichel, 2021). HR managers should also consider using the basic principles of influence (e.g., consistency, social proof and lead by example) to ensure that all employees understand and trust how data is handled, stored, and analysed. Not only does this help build an understanding of how to engage with stakeholders in a certain way, but it also reduces the potential for future conflict.

Taken together, companies should strategically hire people with these four essential skills to effectively use available data and information to achieve HR goals. Ultimately, HR analytics provides managers with the facts, evidence and predictions, which is an important factor in quality decision making that is free from unconscious bias and emotion.

17.0. Industry and practical implications

An As an HR manager, there are a variety of roles and responsibilities to take on within an organization. From hiring and onboarding new employees, to awarding bonuses and helping employees with their retirement goals, the role of an HR manager is crucial to the overall success of the organization. However, with the increasing number of employee inquiries, it becomes necessary for organizations to find a more efficient way to handle these inquiries. This is where HR analytics technology comes in as a valuable tool for HR management.

HR analytics allow managers to consolidate their decisions by using different combinations of analytics techniques such as descriptive analytics, predictive analytics and prescriptive analytics. These techniques provide insights that would otherwise be overlooked, making it easier for managers to make better and more accurate decisions. Additionally, by making more accurate performance evaluations, managers can make fairer and more accurate decisions when awarding variable pay, which in turn increases employee motivation and satisfaction. This increased motivation and satisfaction can lead to a competitive advantage for the organization, resulting in better business performance.

However, based on the evaluation for both quantitative and qualitative analyses of this thesis, it is important to note that simply deploying HR analytics will not automatically improve the overall HR function of the organization. Organizations should figure out how best to use HR analytics in the context of their specific environment, taking into consideration factors such as the organization's size, location, and industry trends. Additionally, organizations need to have the knowledge and capability to leverage existing data, as well as the right regulations in place for data collection, storage, and analysis (Angrave et al., 2016; Stone & Lukaszewski, 2009; Vargas et al., 2018).

For the above reasons, it is reasonable to believe the use of HR analytics is more appropriate for organizations that follow the ideology of contingency and configuration theories, rather than the universalist theory. The reason being that the most appropriate use of HR analytics depends on the context of the situation, and adopting a single, rigid style is not efficient in achieving a positive impact on organizational performance. Ultimately, while HR analytics can be a powerful tool in improving organizational performance, it is not a one-size-fits-all solution and should be used strategically and in conjunction with other HR practices.

18.0. Summary

Overall, this section has succeeded in gaining and providing a more nuanced understanding of the role of HR analytics and HR artificial intelligence in companies. Specifically, it sheds light on 1) which company characteristics are more likely to adopt HR analytics and HR artificial intelligence; 2) what challenges organizations may encounter when using HR analytics and HR artificial intelligence; 3) the key reasons why organizations adopt HR software; 4) what are the latest trends in the software industry, and 5) what are the four essential qualities that users need when implementing HR analytics and HR artificial intelligence. Moreover, the rationale for each decision is clearly presented and justified. For example, when deciding which interview method was most appropriate for the research questions, the semi-structured interview was considered the best because it had the right balance between structured questions and knowledge sharing (i.e., respondents could talk about their own knowledge and experience surrounding the topic). Besides, both inductive and deductive approaches were assessed prior to the coding process, which was an important step in ensuring that meaningful insights were gained from the interview transcripts. Other elements such as target population, interview guide, data analysis, interview findings and discussion were also included successfully in the section.

19.0. Conclusion

To sum up everything above, HR analytics has increased in recent years and the strategic importance of the field of HR is also increasing (Ben-Gal, 2019; Marler and Budreau, 2017; Rasmussen and Ulrich, 2015). One of the reasons is that organizations starting to realize that human capital is an important organizational asset and its centrality is becoming higher (Ben-Gal, 2019; Bontis and Fitz-enz, 2002). The second reason would be the increasing availability of readily available HR data that was previously unavailable (Strohmeier, 2020). The third reason is that decisions made using HR analytics might improve the outcomes in employee performance appraisal, fairness of organizational decisions and so on.

The first part of this study made substantial and influential contributions to the field of HR analytics by revealing that factors such as employee motivation, the use of HR analytics, and variable pay systems (i.e., “pay linked to individual performance” and “pay linked to firm performance”) were found to be critical in a firm’s financial returns. As for the interaction effects analysis, the results of the analysis revealed no interaction effects in the evaluation of employee motivation levels, the type of variable pay systems, and the use of HR analytics. This interpretation of the statistical models suggests the relationship between these three variables can be more complicated than the initial thought.

In terms of the qualitative part of the study, it helps to reinforce and provide a comprehensive understanding of why and how a company's financial performance can be highly dependent on a company’s ability to deploys its HR analytics system. In other words, it accomplished the task by highlighting some of the key areas a company needs to pay special attention to in order to maximize the chances of gaining a competitive advantage (i.e., firm characteristics, challenges, key reasons to adopt HR software, new trends and user traits). Overall, the scope and depth of the investigatory framework have fostered a more nuanced and inter-connected understanding of the role of HR analytics in organizations.

Chapter 5: General Conclusion

1.0. Conclusion

The concept of HR analytics has grown in importance in recent years (Ben-Gal, 2019; Marler and Budreau, 2017; Rasmussen and Ulrich, 2015). One explanation is that organizations are beginning to realize that human capital is an important organizational asset that is becoming increasingly central (Ben-Gal, 2019; Bontis and Fitz-enz, 2002), and the increasing availability of readily available HR data that was previously unavailable is driving the use of HR analytics (Strohmeier, 2020).

Results were compared and contrasted with those in the literature to illustrate key contributions and advances from previous chapters. This work has provided significant and impactful empirical insights in three areas. Specifically, 1) in developing a more systematic and coherent definition of HR analytics and artificial intelligence in HR, 2) in assessing the implications and impact of artificial intelligence, Big Data, and analytics in HR, 3) and in understanding the industry's experience with implementing and using HR analytics. Besides, the data for the analyses were taken from the European Company Survey (ECS) 2019, covering 28 European countries and over 20,000 sample cases at the firm level, such as human resource management, skills utilization, skills strategies, digitalization, direct employee involvement and social dialogue. The thesis has succeeded in generating a wealth of insights and knowledge derived from the theoretical analytical framework.

The first part of this thesis made a significant and influential contribution to the field of HR analytics by reviewing the relevant literature and providing a more systematic and coherent definition of HR analytics and HR artificial intelligence. Many of the concepts, including the definition, are relatively new in HRM (Falletta & Combs, 2020; Marler & Boudreau, 2017; Van der Laken, 2018; Greasley & Thomas, 2020). The term “HR analytics” might be used simultaneously with “artificial intelligence” by some researchers (Giermindl et al., 2021). A group of researchers might define HR analytics as a calculation process that includes “statistical techniques, machine learning methods, and data mining models that analyse and extract existing and historical facts to make predictions” (Mishra et al., 2016, p.33). However, other scholars might define the term as more general from an HR standpoint (Hoffman et al., 2018; Lawler et al., 2004; Marler & Boudreau, 2017; Van den Heuvel & Bondarouk, 2017). After systematically examining all the necessary literature and the meaning of the different definitions in the HR literature described above, a more coherent working definition of HR analytics considering all aspects of analytics has been developed successfully based upon the INFORMS definition (Smith, 2020), in whicha HR analytics refers to the use of data and predetermined rules to perform analysis to identify useful information to improve management decision making. The focus is on using a varying combination of analytics techniques to improve organizational performance, from tracking information patterns with descriptive analytics, forecasting with predictive analytics, and developing recommended action plans with prescriptive analysis.

In terms of HR artificial intelligence, a working definition emphasizes the concept of automation, which is identified as the distinguishing theme between HR artificial intelligence and HR analytics. For example, Eubanks (2019) proposed that some companies are using HR artificial intelligence (e.g., facial recognition) to automatically calculate employee attendance for their payroll system, whilst other researchers also suggested that HR artificial intelligence such as Natural Language Processing (NLP) can be utilized for recruitment and selection process (Russell & Norvig, 2016; Spitzer et al., 2014). Therefore, this thesis proposes that HR artificial intelligence refers to the ability of computer systems or applications to support and manage HR decisions, whereas the system can automatically improve and handle HRM functions. For example, organizations can adopt sentiment analysis to strengthen their decisions in job interviews or to use NLP with machine learning to verify that their job advertisements are free of unconscious bias.

Study two arose from a desire to gain a more holistic perspective on the factors that influence the adoption of HR analytics in organizations. This thesis adopted a multilevel logistic model with a list of factors from the ECS to evaluate whether there are differences in the adoption of HR analytics between firms. The results suggested that firm-specific factors are important in explaining why firms do or do not make use of HR analytics to monitor the performance of employees. Among various firm-specific factors that matter, most notably firm size and firm age were found to be decisive. Moreover, in assessing whether there are differences in the implementation of HR analytics among the four variable pay systems. The results of the analysis revealed that, on average, companies that use the “payment by results” scheme are more likely to incorporate HR analytics while the results for “pay linked to individual performance” were moderately strong. Besides, the results also revealed that the number of variable pay systems that companies used plays a role. More precisely, the more complex the firms’ processes and organizational structures, the higher the incidence of HR analytics.

As regards to the country context, the results revealed that juridico-political differences, that is differences in the legal ability and opportunity of firms to collect and store data and therefore make efficient use of HR analytics, are able to explain some differences in what factors influence the use of HR analytics from a company perspective. More precisely, the results showed that firms embedded in countries with more liberal regulations on data and privacy protection, which widen (HR) management prerogatives and opportunities to make use of HR analytics to monitor the performance of employees, make more use of HR analytics than firms in countries in which HRM is faced with more regulatory constraints.

The study three, part 1 aims to provide a comprehensive view of the relationship between different kinds of factors at different analytical levels and their interplay in a firm’s financial return. The results of the analysis showed that organizational practices (i.e., firm-specific practices) such as HR analytics could be one of the reasons why a better financial return can be achieved for the company. It is believed that companies that use HR analytics achieve higher financial returns because HR analytics improves the ability of managers to support their decisions with facts and data, resulting in better decisions based on evidence and statistical analysis rather than subjective opinions.

As far as employee-specific factors are concerned, the results revealed that the level of employee motivation in companies is an important reason why companies have an advantage over their competitors. More specifically, the more motivated the employees in the firm, the higher the firm's expected financial return could be, as motivation can serve as a means to reinforce employees' good behaviours and performance, and increase employees' loyalty to create a cohesive force that helps maintain the stability of the company (Stone et al., 2020).

With regard to variable pay systems, the results showed that among the four-variable pay systems, only "pay linked to individual performance" and "pay linked to firm performance" were related to firm financial performance. Besides, all models for variable "pay linked to company performance" were found to be highly significant. In addition, the results suggested that the variable pay systems do indeed contribute to corporate financial performance, with companies that use one to three types of variable pay achieving higher returns than their counterparts.

In addition, this paper systematically analysed the role and relevance of variable pay systems, HR analytics and employees' motivation on firms' financial performance using an interaction effect analysis (i.e., study three, part 2). The initial hypothesis was that HR analytics would act as a moderator to strengthen the relationship between the independent variable (i.e., the number of variable pay systems to use) and the mediator variable (i.e., motivation) as HR analytics helps managers consolidate their decision based on facts and data in employee performance evaluation. The level of motivation among employees depends on the number of variable pay systems an organization uses. However, the results of the analysis did not identify any interaction effect when comparing the different combinations of motivation levels, the number of variable pay systems and the use of HR analytics.

For the qualitative findings, this research contacted forty-two companies. However, there were only eleven companies took part in this qualitative sampling. This reflects the relative difficulty of getting software providers to participate during the national lockdown that began in March 2020, when most organisations were trying to cope with new ways of working and many companies across the UK had moved to work from home. However, the study provides additional support for five specific areas, namely *firm characteristics*, *challenges*, *key reasons to adopt HR software*, *new trends and user traits* in HR analytics and HR artificial intelligence.

Regarding firm characteristics, all respondents seem to agree that there is no particular size or industry that would be more likely to choose HR analytics and artificial intelligence. Different software capabilities are thought to be needed for different phases of the business, (i.e., growth, maturity, and decline) (Baird & Meshoulam, 1998). Besides, the results of the interview also demonstrated that some interviewees' clients did not have the appropriate knowledge to understand and implement HR analytics. Some employees even tried to find excuses to avoid using such software because they are afraid of being replaced. The findings also show that there are some reasons that explain why certain companies are using HR analytics and HR artificial intelligence. Firstly, HR software allows managers to track and evaluate employee performance in a new way that was not possible before. Moreover, HR analytics and HR artificial intelligence can act as a point of contact for employees when HR managers are too busy to handle other HR-related issues. As for the trend in the HR software industry, most respondents agreed that the next trend in HR analytics and HR artificial intelligence will be primarily focused on automated processes for handling organizational tasks.

In addition, based on the results of the interviews and literature review, this thesis identified four fundamental qualities that are essential for HR analytics users, being realization, collaboration, analytics and influence skills.

Overall, the breadth and depth of the research framework contributed to a more nuanced and interconnected understanding of the role of HR analytics and artificial intelligence in organizations. Ultimately, this dissertation was theoretically driven and based on high-quality literature. The methods were carefully selected to fit the unique research questions on various topics in HR analytics. A number of substantive findings are presented that provide corroborating, refuting, or advanced results as a springboard for future discussions. In the end, this PhD thesis was theoretically driven, based on good quality literature, and methodologies were carefully chosen to fit with the unique research questions on various topics of HR analytics. A host of substantive findings will be presented that provide corroborating, refuting, or progressive results as a stepping stone for future discussion.

2.0. Limitation

While the above findings make a significant and noteworthy contribution to the field of HRM, it is equally important to point out some limitations of this research. For the quantitative sections, the ECS's data were collected in numerical form. This has the advantage of providing a standardized format that allows researchers to provide a snapshot of how organizations view HR analytics. However, the results obtained from the quantitative data did not include too many considerations and details about how certain answers were chosen by respondents, and the lack of personalization to further discuss the questions also risks not capturing the big picture between variables. Moreover, variables measuring the quality of the relationship between management and employees may create a social desirability bias by over-reporting "good behaviour" to benefit the company (Lelkes et al., 2012). Some companies might deny the fact that they have “never” or “less than others” about the frequency of giving out rewards because it might reflect poorly on their management practices and ultimately on their organizational reputation. Besides, it is also important to note that the impact of the country factor should be interpreted with caution, as the survey only includes countries in Europe and the small interclass differences between the variables that could affect our ability to interpret the picture of how companies implement HR analytics. This could therefore be improved by including more countries outside Europe and conducting additional analysis to ensure that the results are consistent and accurate.

As for the qualitative perspective, the interview part complimented and consolidated the findings of the study by assessing the interviewees’ perceptions of HR analytics and HR artificial intelligence, which goes beyond the idea of standardized data collection and statistical comparison. However, the downside of having interviews is that it was difficult to gain insights from a small sample group, and different interviewees may have different views on the topic, especially that HR analytics and HR artificial intelligence is a new area in HR and conclusive judgments are not easy to make. Moreover, questions about the interviewee company’s software could also lead to an unconscious bias by overstating the “usefulness of the software” in favour of the company, which naturally leads to less accurate information than if the question had been posed to an external reviewer. Despite the shortcomings on both the qualitative and quantitative sides. This study reflected considerable detail and precision contributions to the field of HRM.

3.0 Research ideas

In addition, during the course of the research, a number of improvements were identified that would be beneficial for future research. As mentioned in the section above, the inclusion of additional companies from different countries in the analysis could provide a more comprehensive picture of the concept of HR analytics and artificial intelligence in HR. It also provides an opportunity to explore whether there are differences in company characteristics and culture-specific factors such as collectivism and individualism across regions. Furthermore, as for the benefits of HR analytics and HR artificial intelligence software, subsequent research could be conducted longitudinally to investigate whether HR analytics and HR artificial intelligence software can act as a catalyst to facilitate the HR function, especially if HR analytics might require some time to be introduced in the company to see the big effects. Similarly, a more specific survey targeting HR analytics and HR artificial intelligence users would be beneficial to consolidate the use of HR analytics and HR artificial intelligence software. In-depth interviews with HR analytics users are needed to explain how software can maximise HR as a strategic partner in the organization, and possible ways to mitigate negative impacts. For example, the use of HR analytics and HR artificial intelligence may place additional stress on employees due to the rapidly changing learning environment, where employees may need to undergo additional training to become familiar with the technology (see example: Bondarouk & Brewster, 2016; Baruch & Vardi, 2016). Last but not least, further research can explore how HR analytics and artificial intelligence can act as a tool to reduce the agency behaviour between workforce and managers, in which researchers believe that the agency problem is one of the most important elements that companies need to manage appropriately (Boxall & Purcell, 2003; Wood et al., 2014). Questions such as how HR analytics and HR artificial intelligence can improve the transparency of knowledge sharing and reduce the knowledge gap between shareholders, and whether there is a difference in performance between employees when they are selected based on HR analytics and HR artificial intelligence versus traditional methods would be worth exploring.

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Appendices

Appendix 1: Result Table – Study two

	Model 1			Model 2			Model 3			Model 4			Model 5		
	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p
Independent variables															
Organizational factors															
Company size															
10-19 employees (Ref)															
20-49 employees	0.174	0.044	0.001	0.128	0.045	0.010	0.056	0.046	> 0.050	0.061	0.046	> 0.050	0.042	0.047	> 0.050
50-249 employees	0.595	0.046	0.001	0.502	0.047	0.001	0.345	0.051	0.001	0.355	0.051	0.001	0.316	0.054	0.001
250-499 employees	0.725	0.078	0.001	0.584	0.080	0.001	0.384	0.085	0.001	0.396	0.085	0.001	0.317	0.087	0.001
500 or more employees	0.892	0.091	0.001	0.754	0.093	0.001	0.554	0.100	0.001	0.563	0.100	0.001	0.488	0.102	0.001
Firm age	-0.002	0.001	0.010	-0.001	0.001	0.050	-0.001	0.001	0.050	-0.001	0.001	0.050	-0.002	0.001	0.010
Rewards practices: Monetary rewards															
Never (Ref)															
Very often	0.675	0.086	0.001	0.580	0.087	0.001	0.571	0.087	0.001	0.561	0.088	0.001	0.538	0.089	0.001
Fairly often	0.496	0.070	0.001	0.426	0.071	0.001	0.403	0.071	0.001	0.399	0.072	0.001	0.385	0.073	0.001
Not very often	0.281	0.067	0.001	0.225	0.068	0.001	0.208	0.068	0.010	0.206	0.068	0.010	0.197	0.069	0.010
Type of variable pay systems															
Pay by results	0.031	0.011	0.010	0.031	0.011	0.010	0.031	0.011	0.010	0.031	0.011	0.010	0.027	0.011	0.050
Pay by individual performance	0.022	0.011	0.050	0.024	0.011	0.050	0.022	0.011	0.050	0.022	0.011	0.050	0.021	0.011	> 0.050
Pay by team performance	0.009	0.012	> 0.050	0.003	0.012	> 0.050	0.004	0.012	> 0.050	0.003	0.012	> 0.050	-0.000	0.012	> 0.050
Pay by company performance	-0.006	0.009	> 0.050	-0.006	0.009	> 0.050	-0.006	0.009	> 0.050	-0.006	0.009	> 0.050	-0.009	0.009	> 0.050
Number of pay system a company use															
None at all (Ref)															
Single pay system	0.091	0.092	> 0.050	0.078	0.093	> 0.050	0.079	0.093	> 0.050	0.079	0.093	> 0.050	0.061	0.094	> 0.050
Two pay systems	0.162	0.061	0.010	0.145	0.061	0.050	0.140	0.061	0.050	0.142	0.062	0.050	0.141	0.062	0.050
Three pay systems	0.365	0.056	0.001	0.326	0.056	0.001	0.310	0.056	0.001	0.313	0.057	0.001	0.308	0.057	0.001

Four pay systems	0.468	0.061	0.001	0.417	0.061	0.001	0.413	0.061	0.001	0.417	0.061	0.001	0.403	0.062	0.001
Change in the ownership															
No (Ref)															
Yes, and it involved a change of management				0.258	0.054	0.001	0.255	0.054	0.001	0.253	0.055	0.001	0.256	0.055	0.001
Yes, but management remained the same				0.109	0.055	0.050	0.104	0.055	> 0.050	0.105	0.055	> 0.050	0.108	0.056	> 0.050
Team work between employees															
No team (Ref)															
Single team				0.464	0.045	0.001	0.427	0.045	0.001	0.421	0.045	0.001	0.397	0.046	0.001
More than a team				0.579	0.050	0.001	0.541	0.050	0.001	0.537	0.050	0.001	0.496	0.050	0.001
Complexity of hierarchical levels															
No hierarchical levels (Ref)															
Two hierarchical levels							0.396	0.113	0.001	0.392	0.114	0.001	0.384	0.115	0.001
Three hierarchical levels							0.630	0.107	0.001	0.627	0.107	0.001	0.614	0.109	0.001
Four hierarchical levels							0.845	0.113	0.001	0.840	0.113	0.001	0.816	0.115	0.001
Five hierarchical levels							0.836	0.143	0.001	0.822	0.143	0.001	0.788	0.145	0.001
Six hierarchical levels							0.305	0.222	> 0.050	0.302	0.222	> 0.050	0.281	0.224	> 0.050
Relationship with manager															
Very bad (Ref)															
Very good										0.032	0.436	> 0.050	-0.001	0.439	> 0.050
Good										-0.004	0.435	> 0.050	-0.020	0.438	> 0.050
Neither good nor bad										-0.013	0.437	> 0.050	-0.025	0.440	> 0.050
bad										-0.039	0.466	> 0.050	-0.054	0.469	> 0.050
Number of managers															
None at all (Ref)															
less than 20%													0.178	0.092	> 0.050
20% to 39%													0.061	0.105	> 0.050
40% to 59%													-0.089	0.219	> 0.050
60% to 79%													-0.377	0.332	> 0.050
80% or more													-0.049	0.331	> 0.050
Require continuous training															
None at all (Ref)															

less than 20%													0.301	0.064	0.001
20% to 39%													0.329	0.069	0.001
40% to 59%													0.518	0.076	0.001
60% to 79%													0.632	0.080	0.001
80% or more													0.809	0.072	0.001
Market factors															
Competitiveness															
Not at all competitive (Ref)															
Very competitive				0.737	0.125	0.001	0.745	0.125	0.001	0.739	0.126	0.001	0.696	0.126	0.001
Fairly competitive				0.534	0.124	0.001	0.548	0.124	0.001	0.546	0.125	0.001	0.519	0.125	0.001
Not very competitive				0.227	0.132	> 0.050	0.241	0.133		0.242	0.133	> 0.050	0.228	0.133	> 0.050
Company sector															
Art, entertainment & recreation (Ref)															
Mining & quarrying	0.734	0.272	0.010	0.752	0.279	0.010	0.745	0.280	0.010	0.771	0.281	0.010	0.867	0.281	0.010
Manufacturing	0.849	0.124	0.001	0.789	0.126	0.001	0.778	0.126	0.001	0.805	0.127	0.001	0.853	0.128	0.001
Electricity, gas & steam supply	0.142	0.232	> 0.050	0.192	0.234	> 0.050	0.166	0.234	> 0.050	0.200	0.235	> 0.050	0.159	0.236	> 0.050
Water, Sewerage activities	0.344	0.184	> 0.050	0.464	0.187	0.050	0.452	0.187	0.050	0.478	0.188	0.050	0.469	0.188	0.050
Construction	0.248	0.133	> 0.050	0.152	0.135	> 0.050	0.145	0.135	> 0.050	0.171	0.136	> 0.050	0.186	0.137	> 0.050
Wholesale, retail trade, repair of motor & motorcycles	0.954	0.126	0.001	0.843	0.128	0.001	0.846	0.128	0.001	0.873	0.129	0.001	0.880	0.130	0.001
Transportation & Storage	1.067	0.136	0.001	1.037	0.138	0.001	1.075	0.138	0.001	1.103	0.139	0.001	1.053	0.140	0.001
Accommodation & food service	0.493	0.140	0.001	0.384	0.142	0.010	0.373	0.142	0.010	0.395	0.143	0.010	0.444	0.144	0.010
Information & communication	0.917	0.144	0.001	0.766	0.146	0.001	0.797	0.146	0.001	0.821	0.147	0.001	0.724	0.149	0.001
Financial & insurance	1.217	0.165	0.001	1.085	0.167	0.001	1.091	0.167	0.001	1.117	0.168	0.001	0.978	0.169	0.001
Real estate services	0.064	0.214	> 0.050	0.055	0.216	> 0.050	0.050	0.216	> 0.050	0.077	0.217	> 0.050	0.057	0.218	> 0.050
Professional, scientific & technical services	0.967	0.135	0.001	0.846	0.136	0.001	0.857	0.137	0.001	0.881	0.138	0.001	0.777	0.139	0.001
Administrative & support services	0.761	0.153	0.001	0.681	0.155	0.001	0.697	0.155	0.001	0.723	0.156	0.001	0.684	0.157	0.001
Other service activities	0.614	0.131	0.001	0.556	0.132	0.001	0.568	0.132	0.001	0.592	0.133	0.001	0.568	0.134	0.001
Country factors															
Cultural factors															
CME (Ref)															
SME							0.376	0.254	> 0.050	0.379	0.255	> 0.050	0.387	0.263	> 0.050

LME							0.399	0.197	0.050	0.400	0.198	0.050	0.435	0.204	0.050
Constant	-2.555	0.166	0.001	-3.329	0.204	0.001	-4.093	0.257	0.001	-4.118	0.498	0.001	-4.530	0.509	0.001
Country variance constant	0.225	0.063	0.001	0.233	0.065	0.001	0.200	0.056	0.001	0.201	0.056	0.001	0.215	0.060	0.001
Log likelihood	-107925.925			-10629.371			-10581.18			-10564.729			-10423.075		
Wald X^2 (df)	1076.03(30)		0.001	1294.97(37)		0.001	1365.42(44)		0.001	1365.32(48)		0.001	1483.53(58)		0.001
N	18838			18809			18809			18787			18690		

Appendix 2: Result Table – Study three (Main effect)

	Model 1			Model 2			Model 3			Model 4			Model 5		
Independent variables															
Organizational factors															
Company size	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p
10-19 employees (Ref)															
20-49 employees	0.125	0.049	0.050	0.141	0.049	0.010	0.146	0.050	0.010	0.152	0.050	0.010	0.166	0.050	0.001
50-249 employees	0.098	0.053	> 0.050	0.130	0.053	0.050	0.139	0.055	0.050	0.161	0.056	0.010	0.178	0.056	0.010
250-499 employees	0.157	0.096	> 0.050	0.202	0.096	0.050	0.216	0.098	0.050	0.255	0.098	0.010	0.278	0.100	0.010
500 or more employees	0.234	0.119	> 0.050	0.294	0.120	0.050	0.307	0.121	0.050	0.359	0.122	0.010	0.404	0.124	0.010
Firm age	0.000	0.001	> 0.050	0.000	0.001	> 0.050	0.000	0.001	> 0.050	0.000	0.001	> 0.050	0.000	0.001	> 0.050
Change in the ownership															
No (Ref)															
Yes, and it involved a change of management	-0.397	0.059	0.001	-0.394	0.059	0.001	-0.394	0.059	0.001	-0.386	0.059	0.001	-0.396	0.059	0.001
Yes, but management remained the same	0.061	0.066	> 0.050	0.066	0.066	> 0.050	0.066	0.066	> 0.050	0.066	0.066	> 0.050	0.055	0.067	> 0.050
Type of variable payment systems															
Pay by results	-0.004	0.013	> 0.050	-0.004	0.013	> 0.050	-0.004	0.013	> 0.050	-0.005	0.013	> 0.050	-0.012	0.014	> 0.050
Pay by individual performance	0.045	0.013	0.001	0.045	0.014	0.001	0.043	0.014	0.010	0.043	0.014	0.010	0.045	0.014	0.001
Pay by team performance	-0.004	0.015	> 0.050	-0.004	0.015	> 0.050	-0.004	0.015	> 0.050	-0.004	0.015	> 0.050	-0.008	0.015	> 0.050
Pay by company performance	0.129	0.122	0.001	0.128	0.012	0.001	0.127	0.123	0.001	0.127	0.123	0.001	0.125	0.012	0.001
Number of pay system a company use															
None at all (Ref)															
Single pay system	0.356	0.119	0.010	0.339	0.119	0.010	0.339	0.119	0.010	0.337	0.119	0.010	0.331	0.120	0.010

Two pay systems	0.135	0.069	> 0.050	0.139	0.069	0.050	0.136	0.069	0.050	0.140	0.069	0.050	0.147	0.070	0.050
Three pay systems	0.185	0.067	0.010	0.197	0.067	0.010	0.194	0.067	0.010	0.201	0.068	0.010	0.201	0.068	0.010
Four pay systems	-0.001	0.071	> 0.050	0.018	0.072	> 0.050	0.016	0.072	> 0.050	0.028	0.072	> 0.050	0.030	0.073	> 0.050
Frequency providing opportunities for training and development															
Never (Ref)															
Very often	0.283	0.119	0.050	0.329	0.121	0.010	0.328	0.121	0.010	0.279	0.122	0.050	0.268	0.123	0.050
Fairly often	0.105	0.111	> 0.050	0.140	0.112	> 0.050	0.141	0.112	> 0.050	0.102	0.113	> 0.050	0.089	0.114	> 0.050
Not very often	0.009	0.110	> 0.050	0.033	0.110	> 0.050	0.033	0.111	> 0.050	0.005	0.111	> 0.050	-0.007	0.112	> 0.050
Use HR analytics to monitor employee performance															
No, HR analytics (Ref)															
Yes, HR analytics	0.098	0.044	0.050	0.114	0.044	0.010	0.117	0.044	0.010	0.126	0.044	0.010	0.116	0.045	0.010
Employee’s motivation level															
Not at all motivated (Ref)															
Very motivated	0.795	0.172	0.001	0.722	0.174	0.001	0.718	0.174	0.001	0.582	0.182	0.010	0.611	0.183	0.001
Fairly motivated	0.521	0.162	0.010	0.461	0.164	0.010	0.460	0.164	0.010	0.370	0.171	0.050	0.368	0.172	0.050
Not very motivated	0.003	0.164	> 0.050	-0.030	0.165	> 0.050	-0.030	0.165	> 0.050	-0.042	0.170	> 0.050	-0.046	0.171	> 0.050
Frequency of internal hiring															
Never (Ref)															
Always				-0.317	0.082	0.001	-0.315	0.083	0.001	-0.320	0.083	0.001	-0.307	0.084	0.001
Most of the time				-0.263	0.083	0.010	-0.261	0.083	0.010	-0.254	0.083	0.010	-0.248	0.084	0.010
Sometimes				-0.256	0.088	0.010	-0.257	0.088	0.010	-0.242	0.088	0.010	-0.240	0.088	0.010
Rarely				-0.192	0.094	0.050	-0.195	0.094	0.010	-0.179	0.094	> 0.050	-0.182	0.095	> 0.050
Turnover rate															
Very high turnover (Ref)															
High turnover				0.306	0.107	0.010	0.307	0.107	0.010	0.305	0.108	0.010	0.276	0.108	0.010
Low turnover				0.478	0.105	0.001	0.481	0.105	0.001	0.459	0.106	0.001	0.424	0.107	0.001
Very low turnover				0.497	0.115	0.001	0.502	0.116	0.001	0.459	0.117	0.001	0.424	0.118	0.001
Autonomy level in job															
None at all (Ref)															
Less than 20%							0.009	0.074	> 0.050	0.019	0.074	> 0.050	0.012	0.075	> 0.050
20% to 39%							0.018	0.079	> 0.050	0.029	0.079	> 0.050	0.004	0.080	> 0.050

40% to 59%	0.072	0.087	> 0.050	0.085	0.087	> 0.050	0.053	0.088	> 0.050
60% to 79%	0.096	0.093	> 0.050	0.112	0.093	> 0.050	0.091	0.094	> 0.050
80% to 99%	0.080	0.102	> 0.050	0.092	0.102	> 0.050	0.095	0.104	> 0.050
100%	0.029	0.096	> 0.050	0.036	0.096	> 0.050	0.056	0.098	> 0.050
Employee’s involvement plan									
No (Ref)									
Yes	-0.034	0.043	> 0.050	-0.039	0.043	> 0.050	-0.023	0.043	> 0.050
Firm R&D Process									
No (Ref)									
Yes, this is mainly carried out internally				-0.030	0.045	> 0.050	0.001	0.049	> 0.050
Yes, this is mainly carried out in collaboration with one or more other establishments within our company				-0.144	0.106	> 0.050	-0.121	0.107	> 0.050
Yes, this is mainly carried out in collaboration with one or more other companies				-0.073	0.070	> 0.050	-0.065	0.072	> 0.050
Yes, this is mainly contracted out				-0.302	0.131	0.050	-0.312	0.132	0.050
Relationship with manager									
Very bad (Ref)									
Very good				0.516	0.455	> 0.050	0.481	0.459	> 0.050
Good				0.438	0.453	> 0.050	0.399	0.457	> 0.050
Neither good nor bad				0.198	0.454	> 0.050	0.157	0.457	> 0.050
Bad				0.401	0.479	> 0.050	0.366	0.482	> 0.050
Market factors									
Market competitiveness									
Very competitive (Ref)									
Fairly competitive							0.124	0.043	0.010
Not very competitive							-0.048	0.069	> 0.050
Not at all competitive							-0.219	0.141	> 0.050
Company sector									
Art, entertainment & recreation (Ref)									
Mining & quarrying							0.514	0.299	> 0.050
Manufacturing							0.702	0.128	0.001
Electricity, gas & steam supply							0.530	0.244	0.050

Water, Sewerage activities													0.410	0.195	0.050
Construction													0.888	0.136	0.001
Wholesale, retail trade, repair of motor & motorcycles													0.824	0.130	0.001
Transportation & Storage													0.582	0.142	0.001
Accommodation & food service													0.467	0.142	0.001
Information & communication													0.259	0.153	> 0.050
Financial & insurance													1.262	0.216	0.001
Real estate services													1.112	0.237	0.001
Professional, scientific & technical services													0.638	0.145	0.001
Administrative & support services													0.728	0.166	0.001
Other service activities													0.448	0.135	0.001
Country factors															
Cultural factors															
CME (Ref)															
SME							-0.166	0.204	> 0.050	-0.167	0.205	> 0.050	-0.152	0.203	> 0.050
LME							0.196	0.161	> 0.050	0.172	0.162	> 0.050	0.194	0.161	> 0.050
Constant	0.283	0.195	> 0.050	0.122	0.218	> 0.050	0.034	0.246	> 0.050	-0.243	0.487	> 0.050	-0.880	0.506	> 0.050
Country variance constant	0.136	0.040	0.001	0.141	0.042	0.001	0.125	0.037	0.001	0.125	0.037	0.001	0.123	0.037	0.001
Log likelihood	-8469.162			-8445.878			-8442.504			-8424.521			-8357.109		
Wald X^2 (df)	554.63(22)		0.001	597.41(29)		0.001	602.86(38)		0.001	629.24(46)		0.001	748.19(63)		0.001
N	17228			17228			17228			17221			17221		

Appendix 3: Result Table – Study three (Interaction effect)

	Model 1			Model 2			Model 3			Model 4			Model 5		
Using HR analytics & Employees are motivated (Core) & combination of variable pay	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p	γ	s.e.	p
Core	0.036	0.038	> 0.050	0.035	0.038	> 0.050	0.033	0.038	> 0.050	0.030	0.038	> 0.050	0.027	0.038	> 0.050
Results based & core	-0.034	0.063	> 0.050	-0.033	0.063	> 0.050	-0.034	0.063	> 0.050	-0.037	0.063	> 0.050	-0.039	0.062	> 0.050
Individual performance based & core	0.000	0.063	> 0.050	-0.005	0.063	> 0.050	-0.001	0.063	> 0.050	-0.003	0.063	> 0.050	-0.013	0.062	> 0.050
Team performance based & core	0.091	0.093	> 0.050	0.088	0.093	> 0.050	0.094	0.093	> 0.050	0.090	0.093	> 0.050	0.084	0.092	> 0.050

Company performance based & core	-0.067	0.075	> 0.050	-0.074	0.075	> 0.050	-0.074	0.075	> 0.050	-0.080	0.075	> 0.050	-0.077	0.075	> 0.050
Results based & Team performance based & core	-0.042	0.091	> 0.050	-0.041	0.091	> 0.050	-0.034	0.090	> 0.050	-0.037	0.090	> 0.050	-0.029	0.090	> 0.050
Results based & Company performance based & core	-0.063	0.078	> 0.050	-0.071	0.078	> 0.050	-0.076	0.078	> 0.050	-0.083	0.078	> 0.050	-0.072	0.078	> 0.050
Individual performance based & Team performance based & core	0.105	0.099	> 0.050	0.093	0.099	> 0.050	0.103	0.099	> 0.050	0.102	0.099	> 0.050	0.094	0.098	> 0.050
Individual performance based & Company performance based & core	-0.071	0.094	> 0.050	-0.085	0.094	> 0.050	-0.084	0.094	> 0.050	-0.083	0.094	> 0.050	-0.094	0.093	> 0.050
Team performance based & Company performance based & core	-0.088	0.109	> 0.050	-0.091	0.109	> 0.050	-0.090	0.109	> 0.050	-0.094	0.109	> 0.050	-0.089	0.109	> 0.050
Results based & Individual performance based & Company performance based & core	-0.069	0.087	> 0.050	-0.073	0.087	> 0.050	-0.086	0.087	> 0.050	-0.088	0.087	> 0.050	-0.087	0.086	> 0.050
Results based & Team performance based & Company performance based & core	-0.101	0.080	> 0.050	-0.103	0.080	> 0.050	-0.110	0.080	> 0.050	-0.112	0.080	> 0.050	-0.110	0.079	> 0.050
Individual performance based & Team performance based & Company performance based & core	-0.060	0.070	> 0.050	-0.069	0.070	> 0.050	-0.074	0.070	> 0.050	-0.071	0.070	> 0.050	-0.071	0.070	> 0.050
Using HR analytics & Employees are not motivated (Core) & combination of variable pay															
Results based & core	0.001	0.075	> 0.050	0.003	0.075	> 0.050	0.004	0.075	> 0.050	-0.003	0.075	> 0.050	-0.010	0.075	> 0.050
Individual performance based & core	0.084	0.074	> 0.050	0.081	0.073	> 0.050	0.084	0.073	> 0.050	0.083	0.073	> 0.050	0.076	0.073	> 0.050
Team performance based & core	-0.064	0.137	> 0.050	-0.064	0.137	> 0.050	-0.062	0.136	> 0.050	-0.056	0.137	> 0.050	-0.038	0.136	> 0.050
Company performance based & core	-0.004	0.100	> 0.050	-0.007	0.100	> 0.050	-0.001	0.099	> 0.050	-0.006	0.100	> 0.050	0.008	0.099	> 0.050
Results based & Individual performance based & core	-0.037	0.054	> 0.050	-0.035	0.054	> 0.050	-0.039	0.054	> 0.050	-0.037	0.054	> 0.050	-0.032	0.053	> 0.050
Results based & Team performance based & core	-0.152	0.136	> 0.050	-0.157	0.136	> 0.050	-0.150	0.136	> 0.050	-0.109	0.139	> 0.050	-0.093	0.139	> 0.050
Results based & Company performance based & core	0.055	0.105	> 0.050	0.050	0.105	> 0.050	0.054	0.105	> 0.050	0.052	0.105	> 0.050	0.059	0.105	> 0.050
Individual performance based & Team performance based & core	-0.064	0.111	> 0.050	-0.073	0.111	> 0.050	-0.069	0.111	> 0.050	-0.068	0.111	> 0.050	-0.063	0.111	> 0.050
Individual performance based & Company performance based & core	-0.098	0.111	> 0.050	-0.110	0.111	> 0.050	-0.126	0.110	> 0.050	-0.113	0.110	> 0.050	-0.124	0.110	> 0.050
Team performance based & Company performance based & core	0.190	0.167	> 0.050	0.192	0.167	> 0.050	0.189	0.166	> 0.050	0.200	0.166	> 0.050	0.212	0.166	> 0.050
Results based & Individual performance based & Team performance based & core	0.021	0.045	> 0.050	0.021	0.045	> 0.050	0.019	0.045	> 0.050	0.019	0.045	> 0.050	0.018	0.045	> 0.050
Results based & Individual performance based & Company performance based & core	0.039	0.105	> 0.050	0.039	0.104	> 0.050	0.033	0.104	> 0.050	0.027	0.104	> 0.050	0.034	0.104	> 0.050
Results based & Team performance based & Company performance based & core	0.059	0.157	> 0.050	0.049	0.157	> 0.050	0.044	0.157	> 0.050	0.042	0.157	> 0.050	0.041	0.157	> 0.050

Individual performance based & Team performance based & Company performance based & core	0.061	0.116	> 0.050	0.046	0.116	> 0.050	0.033	0.115	> 0.050	0.031	0.115	> 0.050	0.029	0.115	> 0.050
Results based & Individual performance based & Team performance based & Company performance based & core	0.003	0.032	> 0.050	0.002	0.032	> 0.050	0.002	0.032	> 0.050	-0.001	0.032	> 0.050	0.003	0.032	> 0.050
Not using HR analytics & Employees are motivated (Core) & combination of variable pay															
Results based &core	-0.043	0.042	> 0.050	-0.041	0.042	> 0.050	-0.036	0.042	> 0.050	-0.038	0.042	> 0.050	-0.042	0.042	> 0.050
Individual performance based & core	-0.020	0.043	> 0.050	-0.024	0.043	> 0.050	-0.020	0.043	> 0.050	-0.018	0.043	> 0.050	-0.026	0.043	> 0.050
Team performance based & core	-0.003	0.072	> 0.050	-0.003	0.072	> 0.050	0.010	0.072	> 0.050	0.009	0.072	> 0.050	0.000	0.071	> 0.050
Company performance based & core	-0.071	0.056	> 0.050	-0.076	0.056	> 0.050	-0.074	0.056	> 0.050	-0.076	0.057	> 0.050	-0.076	0.056	> 0.050
Results based & Individual performance based & core	-0.057	0.044	> 0.050	-0.056	0.044	> 0.050	-0.052	0.044	> 0.050	-0.050	0.044	> 0.050	-0.047	0.043	> 0.050
Results based & Team performance based & core	-0.082	0.091	> 0.050	-0.079	0.091	> 0.050	-0.066	0.091	> 0.050	-0.068	0.091	> 0.050	-0.067	0.090	> 0.050
Results based & Company performance based & core	-0.092	0.078	> 0.050	-0.095	0.078	> 0.050	-0.091	0.077	> 0.050	-0.094	0.078	> 0.050	-0.088	0.077	> 0.050
Individual performance based & Team performance based & core	-0.004	0.083	> 0.050	-0.009	0.083	> 0.050	0.004	0.083	> 0.050	0.006	0.083	> 0.050	0.000	0.083	> 0.050
Individual performance based & Company performance based & core	-0.087	0.075	> 0.050	-0.099	0.075	> 0.050	-0.099	0.075	> 0.050	-0.096	0.075	> 0.050	-0.100	0.074	> 0.050
Team performance based & Company performance based & core	-0.138	0.108	> 0.050	-0.144	0.108	> 0.050	-0.138	0.108	> 0.050	-0.138	0.108	> 0.050	-0.129	0.107	> 0.050
Results based & Individual performance based & Team performance based & core	-0.025	0.041	> 0.050	-0.022	0.041	> 0.050	-0.016	0.041	> 0.050	-0.013	0.041	> 0.050	-0.012	0.041	> 0.050
Results based & Individual performance based & Company performance based & core	-0.098	0.091	> 0.050	-0.099	0.091	> 0.050	-0.103	0.091	> 0.050	-0.101	0.091	> 0.050	-0.099	0.091	> 0.050
Results based & Team performance based & Company performance based & core	-0.079	0.082	> 0.050	-0.080	0.082	> 0.050	-0.076	0.082	> 0.050	-0.078	0.082	> 0.050	-0.071	0.081	> 0.050
Individual performance based & Team performance based & Company performance based & core	-0.084	0.076	> 0.050	-0.088	0.076	> 0.050	-0.091	0.075	> 0.050	-0.085	0.076	> 0.050	-0.082	0.075	> 0.050
Results based & Individual performance based & Team performance based & Company performance based & core	-0.041	0.037	> 0.050	-0.039	0.037	> 0.050	-0.033	0.036	> 0.050	-0.030	0.036	> 0.050	-0.032	0.036	> 0.050
Not using HR analytics & Employees are not motivated (Core) & combination of variable pay															
Results based & Individual performance based & core	-0.096	0.059	> 0.050	-0.098	0.059	> 0.050	-0.098	0.059	> 0.050	-0.101	0.059	> 0.050	-0.095	0.059	> 0.050
Results based & Team performance based & core	0.147	0.118	> 0.050	0.145	0.118	> 0.050	0.158	0.118	> 0.050	0.160	0.118	> 0.050	0.161	0.117	> 0.050
Results based & Company performance based & core	-0.204	0.108	> 0.050	-0.207	0.108	> 0.050	-0.199	0.108	> 0.050	-0.208	0.108	> 0.050	-0.184	0.107	> 0.050

Individual performance based & Team performance based & core	0.022	0.090	> 0.050	0.017	0.090	> 0.050	0.016	0.090	> 0.050	0.014	0.090	> 0.050	0.009	0.090	> 0.050
Individual performance based & Company performance based & core	-0.150	0.093	> 0.050	-0.164	0.093	> 0.050	-0.167	0.093	> 0.050	-0.163	0.093	> 0.050	-0.169	0.093	> 0.050
Team performance based & Company performance based & core	-0.072	0.138	> 0.050	-0.074	0.138	> 0.050	-0.071	0.138	> 0.050	-0.076	0.138	> 0.050	-0.065	0.137	> 0.050
Results based & Team performance based & Company performance based & core	-0.213	0.149	> 0.050	-0.208	0.149	> 0.050	-0.206	0.149	> 0.050	-0.206	0.149	> 0.050	-0.211	0.148	> 0.050
Results based & Individual performance based & Team performance based & core	-0.001	0.056	> 0.050	0.003	0.056	> 0.050	0.000	0.055	> 0.050	0.001	0.055	> 0.050	0.003	0.055	> 0.050
Results based & Individual performance based & Company performance based & core	-0.117	0.103	> 0.050	-0.120	0.103	> 0.050	-0.133	0.103	> 0.050	-0.131	0.103	> 0.050	-0.123	0.103	> 0.050
Individual performance based & Team performance based & Company performance based & core	0.037	0.097	> 0.050	0.037	0.097	> 0.050	0.035	0.097	> 0.050	0.042	0.097	> 0.050	0.046	0.096	> 0.050
Results based & Individual performance based & Team performance based & Company performance based & core	-0.043	0.050	> 0.050	-0.041	0.050	> 0.050	-0.041	0.050	> 0.050	-0.039	0.050	> 0.050	-0.037	0.050	> 0.050

Appendix 4: HR analytics/ artificial intelligence developer questions – Standard questions

Introduction questions

1.0 Could you please tell me what is your current position in the organisation?

1.1 How long have you been working in this company?

1.2 What are your tasks?

1.3 What is your background? (e.g., IT, management, HRM or other)

2.0 Who are your customers?

2.1 Are they small/ large companies, which industries did they belong to, are they domestic/ multinational companies, other criteria?

2.2 What kind of services did customers expect from you/ your company?

2.3 Did your customers look for solutions for general business operation? Or, did they look for specific product to tackle an area of HRM? (e.g., recruitment, employee engagement or other?)

2.4 Did your customers proactively looking for new ways to carry HRM duties? Or did your customers only look for solutions when they experience problems? (e.g., focus on problem solving VS proactive innovative solutions/ products)

2.5 For which HR functions have you been asked to provide/ develop technical solutions? (e.g., recruitment, selection, performance management, engagement)

2.6 What kind of products did you offer for managing human resource? What kind of technique is used in the solutions? (Predictive analytics, descriptive analytics, prescriptive analytics, facial recognition, natural language processes etc)

3.0 Did your customers have clear expectations (idea) about what they are looking for when they contacted you? Or, did your customers looking for advices and suggestions?

3.1 How much freedom (flexible/ customisable) did you have when developing products for your customers?

3.2 How would you describe the services/ products development process? Specifically, the involvement of your customers and the customer's company. (e.g., site visit before suggesting solutions)

4.0 What are the problems/ challenges faced by your customers when they have started to using the product?

4.1 What did your customers want to achieve by using the products/ services?

4.2 How can the products/ services enable customers to achieve the goal?

4.3 What are the factors promoting the creation of 'good' solutions to the problems/ innovative products? (e.g., relationship, good communication with customers)

4.4 What are the factors hampering (affect) the creation of 'good' solutions to the problems/innovative products?

5.0 What are the key challenges you/your organisation faces in providing solutions? (e.g., technological limitations, perceived usefulness of technology by customers/ industry, data protection, ethical issues associated with the use of technology).

5.1 Do you aware of any services/products are available but not in use because of the lack of acceptance, technology anxiety, other reasons?

6.0 What are in your opinion the key trends and developments in your industry?

7.0 What kind of products and service can we expect in the near future that can be used in organisation (e.g., HRM)?

Appendix 5: Participant Information Sheet

Participant Information Sheet

Project title: The implications and impact of the artificial intelligence, big data and HR analytics in HRM: A critical analysis of EU enterprise
Researcher(s): Thomas Kiu **Department:** Durham University Business School **Contact details**: chun.t.kiu@durham.ac.uk

Supervisor name: Dr Barbara Bechter and Professor Bernd Brandl **Supervisor contact details**: barbara.bechter@durham.ac.uk and bernd.brandl@durham.ac.uk
You are invited to take part in a research study that I am conducting as part of my PhD.
Before you decide whether to agree to take part it is important for you to understand the purpose of the research and what is involved as a participant. Please read the following information carefully. Please get in contact if there is anything that is not clear or if you would like more information.

What is the purpose of the study?
The aim of this study is to strengthen our understanding why and how businesses can use HR related software to improve HR processes or/ and organisational performance. We are also interested in learning about the latest trends and challenges faced by developers/ vendors.

Why have I been invited to take part?
You have been invited to take part in this research study because your company have either offer HR analytics and/or artificial intelligence services to customers. We would like to strengthen our understanding of how technology can influence HR functions.

Do I have to take part?
Your participation is voluntary and you do not have to agree to take part. If you do agree to take part, you can withdraw at any time, without giving a reason.

What will happen to me if I take part?
If you agree to take part in the study, you will be asked a series of question based on HR analytics and/ or artificial intelligence. This interview will be recorded and take place on Skype. There are total seven questions and we are aiming to finish the interview within 50 minutes.

Are there any potential risks involved?

No, there are no potential risks involved in this study.

Will my data be kept confidential?
All information obtained during the study will be kept confidential. If the data is published, it will be entirely anonymous and will not be identifiable as yours.

What will happen to the results of the project?
Durham University is committed to sharing the results of its world-class research for public benefit. As part of this commitment, Durham University has established an online repository for all Durham University Higher Degree theses which provides access to the full text of freely available theses. The study in which you are invited to participate will be written up as a thesis. On successful submission of the thesis, it will be deposited both in print and online in the University archives, to facilitate its use in future research. The thesis will be published open access.

Moreover, we expect the results to be published by the end of 2021. No personal data will be shared, however, anonymized (i.e. not identifiable) data may be used in publications, presentations, and other research outputs. At the end of the project, anonymized data may be archived and shared with others for legitimate research purposes. All research data and records needed to validate the research findings will be stored for 10 years after the publication of the results.

Who do I contact if I have any questions or concerns about this study?
If you have any further questions or concerns about this study, please speak to the researcher or their supervisor. If you remain unhappy or wish to make a formal complaint, please submit a complaint via the University's Complaints Process.

[-The end-]