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People Analytics: Exploring the Debates, Drivers, and Performance Impact

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DECLARATION

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LIST OF ABBREVIATIONS

ABS: Association of Business Schools

AI: Artificial Intelligence

ANOVA: A One-way Analysis of Variance

AOM: Academy of Management

BI: Business Intelligence

CIPD: Chartered Institute of Personnel and Development

e-HRM: Electronic HRM

EBM: Evidence-based Management

EFA: Exploratory Factor Analysis

EURAM: European Academy of Management

HR: Human Resource

HRIS: Human Resource Information Systems

HRM: Human Resource Management

IAM: Irish Academy of Management

ICT: information and communications technology

IoT: Internet of Things

IT: Information Technology

JQL: Journal Quality List

KPI: Key Performance Indicator

KSAOs: Knowledge, Skills, Abilities, and Other Characteristics

ML: Machine Learning

OLAP: Online Analytical Processing

RBV: Resource-based View of the Firm

SEM: Structural Equation Modelling

VIF: Variance Inflation Factors

ABSTRACT

People analytics has recently become an emerging trend within the field of HRM. Despite the significant growth of people analytics, many questions around people analytics and its performance impact remain unanswered. Drawing on the resource-based view of the firm (RBV, Barney, 1991), evidence-based management (EBM, Rousseau & Barends, 2011), and strategic human capital theory (Becker, 1964), this dissertation seeks to make an original contribution to knowledge by answering the following research questions: (1) What debates and challenges are emerging as a result of people analytics adoption? (2) What factors contribute to the success of people analytics? (3) How does people analytics impact organizational performance?

To do so, the dissertation is organized into three studies, each with its own set of research aims and objectives that logically interconnect to the overarching research questions. In particular, Study 1 presents a systematic literature review addressing the debates and challenges emerging as a result of people analytics adoption. Study 2 aims to address the key knowledge, skills, abilities, and other characteristics (KSAOs) required by HR Analysts through investigating the relationship between analytical and storytelling skills and their impact on individual and team people analytics performance. Finally, Study 3 seeks to understand why, how, and when analytics influence organizational performance. A survey methodology was adopted for Studies 2 and 3.

Overall, the dissertation reveals the current debates and challenges in people analytics and finds strong support for the performance impact of people analytics. This research extends our understanding of people analytics by offering new and original contributions to this field. Similarly, it builds theoretical foundations for the impact of people analytics.

CHAPTER 1 – INTRODUCTION

1.1 Introduction

This chapter first introduces the overall research context of people analytics, presents the overarching research gaps and questions, and illustrates how they are addressed in each of the three studies. Following that, the chapter gives an overview of each study and justifies how the three studies are related and synthesized. Finally, the structure of the thesis is presented, offering an outline of the contents of each chapter.

1.2 Research Context: People Analytics

The human resource (HR) landscape is currently undergoing a significant shift, as evidenced by technological disruptions and the prominence of using big data, artificial intelligence (AI), and machine learning (ML) to make evidence-based decisions (Fernandez & Gallardo-Gallardo, 2020; Harney & Collings, 2021; Minbaeva, 2021; Strohmeier, 2018). This *digital revolution* has led to the rapid growth and adoption of people analytics, a "game-changer" for the future of HR (van der Togt and Rasmussen, 2017, p. 131), offering HR professionals the ability to transform workforce data into actionable insights (Garcia-Arroyo & Osca, 2019; King, 2016; Marler & Boudreau, 2017; McIver, Lengnick-Hall, & Lengnick-Hall, 2018; Sharma & Sharma, 2017; Sivarajah, Kamal, Irani, & Weerakkody, 2017). According to Marler and Boudreau (2017, p. 15), people analytics is *"[a]n 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*".

In recent years, people analytics has attracted the interest of scholars and practitioners due to the opportunity it offers HR departments in making evidence-based decisions (CIPD & WorkDay, 2018; Fernandez & Gallardo-Gallardo, 2020; Huselid, 2018; King, 2016; Kryscynski, Reeves, Stice-Lusvardi, Ulrich, & Russell, 2018; Marler & Boudreau, 2017). From a research perspective, this is evidenced by the recent publication of two special issues focused on the developing field of people analytics. First, in *The Journal of Organizational Effectiveness: People and Organizations* (2017 Volume 4, Issue 2, edited by Dana Minbaeva) and the second in *Human Resource Management* (2018 Volume 57, Issue 3, edited by Mark Huselid). Likewise, recent reviews conducted by Tursunbayeva et al. (2018), Fernandez and Gallardo-Gallardo (2020), and Margherita (2020) have demonstrated the growth of people analytics literature with over 30 articles published in Association of Business Schools (ABS) ranked journals since 2017. In contrast, people analytics has seen even greater interest and adoption in practice. For example, according to a Deloitte (2017) survey of over 10,000 HR professionals in 140 different countries, 71% of respondents identify people analytics as a major trend and a high priority for the foreseeable future. Similarly, professional associations, including the Chartered Institute of Personnel and Development (CIPD) and consulting firms, have begun to publish blogs; white papers; and reports targeted at a practitioner audience, claiming the benefits of leveraging "people data" (CIPD & WorkDay, 2018; Deloitte, 2017, 2018).

Overall, people analytics has attracted increasing attention over the past several years, with HR professionals adopting people analytics to inform evidence-based decision-making. Nonetheless, several research gaps, notably regarding the benefits, debates, challenges, and factors that contribute to the success of people analytics, remain unanswered.

1.3 Research Gaps, Questions, and Objectives

Despite the substantial growth of academic research on the topic, many questions around people analytics and its performance impact remain unanswered, necessitating further scholarly attention. First, while there has been a significant growth of people analytics research and adoption in practice, many scholars have become more skeptical of people analytics questioning its legitimacy and whether HR departments should adopt people analytics altogether (Andersen, 2017; Angrave, Charlwood, Kirkpatrick, Lawrence, & Stuart, 2016; Baesens, De Winne, & Sels, 2017; Levenson & Fink, 2017; Marler & Boudreau, 2017; McIver et al., 2018; Rasmussen & Ulrich, 2015). These concerns emphasize the need to further understand the challenges and debates emerging as a result of people analytics adoption.

Second, although a growing number of case studies and qualitative research projects identify analytical and storytelling skills as the two broad human capital inputs required to perform people analytics, the direct impact of analytical and storytelling skills on enhancing people analytics performance remains unknown (Andersen, 2017; Huselid, 2018; McCartney, Murphy, & McCarthy, 2020; McIver et al., 2018; Minbaeva, 2018; Peeters, Paauwe, & Van De Voorde, 2020).

Third, people analytics has been claimed to allow organizations to improve their performance (Fernandez & Gallardo-Gallardo, 2020; Margherita, 2020; Marler & Boudreau, 2017), however, research demonstrating whether this relationship exists and how it occurs remains unclear. Despite the increase in case studies published demonstrating the impact of people analytics, empirical evidence suggesting the success of people analytics remains rare, with organizations offering little evidence in support of the claims that people analytics can aid in strategic decision making (Baesens et al., 2017; Greasley & Thomas, 2020; Huselid, 2018; Levenson & Fink, 2017; Rasmussen & Ulrich, 2015).

Answering these emerging questions has significant implications for both research and practice. First, it extends our understanding of how people analytics can affect performance and highlights the underlying mechanisms contributing to people analytics performance at the organizational and individual levels. Second, from a practical perspective, it clarifies how and what steps HR departments should take to improve their data-driven decision-making and people analytics performance.

Overall, drawing on the resource-based view of the firm (RBV, Barney, 1991), evidence-based management (EBM, Rousseau & Barends, 2011), and strategic human capital theory (Becker, 1964), which are reviewed in Chapter 2, this dissertation seeks to make an original contribution to knowledge by answering the following overarching research questions:

(1) What debates and challenges are emerging as a result of people analytics adoption?

(2) What factors contribute to the success of people analytics?

(3) How does people analytics impact organizational performance?

1.4 Overview of the Three Studies

This dissertation is organized into three studies, each with its own set of research aims and objectives that logically interconnect to the overarching research questions. In particular, Study 1 presents a systematic literature review addressing the debates and challenges emerging as a result of people analytics adoption. Furthermore, the study also outlines several areas for future research in the field of people analytics. Study 2 aims to address the key knowledge, skills, abilities, and other characteristics (KSAOs) required by HR Analysts through investigating the relationship between analytical and storytelling skills and their impact on individual and team people analytics performance. Finally, Study 3 seeks to understand why, how, and when analytics influence organizational performance. Table 1.1 presents an overview of three studies in terms of research questions, theories, methods and levels of analysis. Additionally, a summary of each study is presented below.

Table 1.1 Overview of the Three Studies

Study	Title	Research Question(s)	Theory	Method	Level of Analysis	Publication Status
1	Promise Vs. Reality: Ongoing Debates in People Analytics	What debates and challenges are emerging as a result of people analytics adoption?	-	Systematic Literature Review	-	• Presented at the European Academy of Management (EURAM) Conference 2021 • R&R (minor revisions) in *Journal of Organizational Effectiveness: People and Performance* (ABS 2)
2	Complementarity Human Capital: Linking Analytical and Storytelling Skills to People Analytics Performance	What is the direct and complementarity effect of analytical and storytelling skills on people analytics task and team performance?	Strategic human capital	Quantitative Survey to People Analytics Professionals	Individual Level	• Presented at the Irish Academy of Management (IAM) Conference 2021
3	Bridging the Gap: Why, How, and When People Analytics Can Impact Organizational Performance	Why, how, and when people analytics leads to increased organizational performance?	Resource-based view of the firm Evidence-based management	Quantitative Survey to HR Managers	Organizational Level	• Presented at the Academy of Management (AOM) Conference 2019 • R&R (major revisions) in *Management Decision* (ABS 2)

1.4.1 Study 1 – Promise Vs. Reality: Ongoing Debates in People Analytics

Enabled by recent advancements in information technology, people analytics has become an emerging trend in human resource management (HRM) (Falletta & Combs, 2020; Huselid, 2018; Margherita, 2020; Marler & Boudreau, 2017). Despite the significant growth of people analytics literature and the continued adoption of people analytics in practice, the challenges and emerging debates attributed to the adoption of people analytics is underdeveloped in the existing people analytics literature. Accordingly, this study aims to address the research question of what debates and challenges are emerging as a result of people analytics adoption. In response to this question, this study conducts a systematic literature review of 42 peer-reviewed articles focused on people analytics published in ABS ranked journals between 2011 and 2020.

The review finds five themes illustrating emerging challenges within the people analytics literature, including (1) the inconsistency among the concept and definition of people analytics, (2) people analytics ownership debate, (3) ethical and privacy concerns of using people analytics, (4) missing evidence of people analytics impact, and (5) readiness to perform people analytics. This systematic review offers insight into what debates and issues are emerging as a result of people analytics adoption. Furthermore, it advances people analytics research by presenting a comprehensive research agenda and roadmap for collaboration between scholars and practitioners.

1.4.2 Study 2 – Complementarity Human Capital: Linking Analytical and Storytelling Skills to People Analytics Performance

Despite the growing number of case studies and qualitative research projects that identify analytical and storytelling skills as the two broad human capital inputs required to perform people analytics, the direct impact of analytical and storytelling skills on enhancing people analytics performance remains unknown (Andersen, 2017; Huselid, 2018; McCartney et al., 2020; McIver et al., 2018; Minbaeva, 2018; Peeters et al., 2020). As such, this study draws on the strategic human capital literature to hypothesize that analytical and storytelling skills are both independent human capital inputs contributing to the success of people analytics. Furthermore, this study draws on the human capital resource framework (Ployhart, Nyberg, Reilly, & Maltarich, 2014) and theorizes that when analytical and storytelling skills are combined, they create a complementarity interaction that leads to increased task (e.g., fulfilling responsibilities and completing people analytics tasks) and team performance (e.g., providing feasible recommendations) for HR Analysts.

A sample of 173 people analytics professionals is used to test each hypothesis and illustrate the complementarity human capital relationship. The results suggest that storytelling skills are positively associated with people analytics task and team performance. In addition, a complementarity effect was found whereby storytelling skills strengthen the positive impact of analytical skills on individual people analytics task performance and team performance. The study makes two significant contributions to the fields of people analytics and strategic human capital. First, the study responds to several calls for research investigating the KSAOs most influential to people analytics performance. Second, the study extends the current understanding of the direct and complementarity impact of human capital on performance.

1.4.3 Study 3 – Bridging the Gap: Why, How, and When People Analytics Can Impact Organizational Performance

Despite the growth and adoption of people analytics, it remains unknown whether and how people analytics can impact organizational performance. This study draws on RBV (Barney, 1991), dynamic capabilities (Teece, Pisano, & Shuen, 1997), and EBM (Bezzina, Cassar, Tracz-Krupa, Przytuła, & Tipurić, 2017; Rousseau & Barends, 2011), and theorizes why, how, and when people analytics can positively impact organizational performance. To do so, data were collected from 155 Irish organizations to test a moderated mediation model linking HR technology, people analytics, EBM, and organizational performance. The study's findings support the proposed moderated mediation model, suggesting that people analytics positively impacts organizational performance through its EBM capability. Further, the results indicate that HR technology enables people analytics and strengthens the impact of people analytics on EBM.

This study extends our understanding of why and how people analytics leads to higher organizational performance by theorizing and identifying EBM as a mediator between people analytics and organizational performance. Additionally, this study addresses the conditional effect of HR technology in enabling people analytics and moderating the link between people analytics and EBM. Finally, this study contributes to people analytics research by revealing and investigating people analytics' performance impact on the underlying mechanism (EBM) and boundary conditions (HR technology).

1.4.4 Synthesis of the Three Studies and Original Contribution to Knowledge

Overall, the studies address three research questions. Study 1 (systematic literature review) addresses the questions of what debates and challenges are emerging as a result of people analytics adoption. In addition, the review discusses several areas for future research in the field of people analytics. The subsequent two studies then focus on addressing key areas of future research identified in the first study. For instance, as demonstrated in the systematic literature review as well as recent literature in people analytics (Andersen, 2017; Ellmer & Reichel, 2021; Huselid, 2018; McCartney et al., 2020; Minbaeva, 2018; Peeters et al., 2020), future research is required to address the KSAOs that are most impactful concerning people analytics performance. Drawing on the strategic human capital literature, Study 2 builds on the findings from Study 1 by investigating the impact of analytical and storytelling skills and their complementarity effect on people analytics performance. Doing so offers insight into the second research question of the underlying mechanisms that facilitate people analytics performance, finding that analytical and storytelling skills contribute to individual and team people analytics performance.

Based on the findings in Studies 1 and 2, Study 3 addresses the performance impact of people analytics and explores the underlying mechanisms that facilitate people analytics performance. As shown in Study 1, the majority of people analytics research to date has focused on the application of people analytics with little evidence supporting the link between people analytics and organizational performance (Baesens et al., 2017; Greasley & Thomas, 2020; Huselid, 2018; Levenson & Fink, 2017; Marler & Boudreau, 2017; Rasmussen & Ulrich, 2015). As such, it remains unknown how people analytics contributes to organizational performance. Study 3 addresses this gap by theorizing a moderated mediation model that links people analytics with organizational performance through the mediating role of EBM, moderated by HR technology. Furthermore, Study 3 builds on Study 2 by moving from individual-level people analytics performance to organizational-level people analytics outcomes.

As can be seen, Study 1 acts as the foundation of the dissertation, with the following two studies building on its findings and conclusions. Collectively, the three studies that this dissertation comprises of make original contributions to knowledge in the field of people analytics by addressing the research questions proposed in this dissertation.

1.5 Thesis Structure and Outline

Chapter One first introduces the three-study dissertation, outlining the overall research context of people analytics and the overarching research gaps and questions that underpin each study. Following that, the chapter illustrates the relationship between each study while also providing a brief overview of each study. Finally, the structure of the thesis is presented, offering an outline of the contents of each chapter.

Chapter Two focuses on presenting a broad overview of the core topics featured in the dissertation. First, the concept of people analytics is introduced, outlining how people analytics is defined and is discussed within the context of the dissertation. Second, the driving forces shaping the adoption and implementation of people analytics are explored. Next, applications of people analytics are presented, offering insight into how HR departments are currently using people analytics to make evidence-based decisions. Finally, the research gaps are provided and how the three studies individually and collectively address these research gaps are presented.

Chapter Three presents the first of the three studies within the dissertation entitled "*Promise Vs. Reality: Ongoing Debates in People Analytics*". This systematic literature review aims to discuss the debates and challenges that have arisen as a result of the adoption and implementation of people analytics and provide a specific research agenda for the future of people analytics. This systematic review serves as the foundation of the dissertation. First, an overview is presented, offering context into the current state of people analytics. Next, the methodology section outlines the search process, including the rationale for the databases referenced, the keywords identified, and the criteria used in selecting the appropriate articles. Additionally, the methodology section offers an evaluation of the selected articles, along with a description of the coding process. The research findings are then presented, outlining the themes associated with the debates and challenges emerging as a result of people analytics adoption. Lastly, the discussion and conclusion sections critically evaluate each theme and sets an agenda for future research in people analytics.

Chapter Four presents the second study entitled "*Complementarity Human Capital: Linking Analytical and Storytelling Skills to People Analytics Performance*". The study focuses on answering whether analytical and storytelling skills influence individual and team-level people analytics performance. Furthermore, the study aims to determine whether combined analytical and storytelling skills can create a complementarity human capital resource leading to higher overall people analytics performance. This study is organized as follows: first, the literature review and hypotheses section summarizes the existing research in people analytics, human capital resources, and human capital complementarities while outlining the hypotheses tested within the study. Next, the research methodology outlines the data collection process and the profile of the study's participants and explains the survey measures. Then, the research findings are presented, including the measurement and structural models and analysis for each hypothesis tested. Finally, the study's theoretical and practical contributions and its limitations and future research directions are discussed.

Chapter Five presents the final study entitled “*Bridging the Gap: Why, How, and When People Analytics Can Impact Organizational Performance*”. This study aims to understand how and why people analytics influences organizational performance and uncover the mechanisms through which this increased performance occurs. First, the literature review and hypotheses development section summarizes the existing research in people analytics while outlining the four hypotheses tested within the study. Second, the research methodology describes the data collection process and offers a detailed explanation of the survey measures. Next, the research findings are presented, providing analysis and support for each of the hypotheses tested. Lastly, the study's theoretical contributions to people analytics and EBM are presented, implications for practice, limitations, and areas for future research are discussed.

Chapter Six discusses the theoretical contributions made by each of the three studies in this dissertation. Practical implications, limitations of the dissertation, and areas for future research are also addressed.

Finally, *Chapter Seven* concludes with a brief and general conclusion. This chapter reiterates the relationship between each study, the overarching research gaps, and the questions that underpin the dissertation.

Chapter 2 – Literature Review

2.1 Introduction

This chapter focuses on presenting a broad overview of the core topics featured in the dissertation. First, the concept of people analytics is introduced. Second, the driving forces shaping the adoption and implementation of people analytics are explored theoretically and technologically. Next, applications of people analytics are presented, offering insights into how people analytics has been used to make evidence-based decisions. Finally, the research gaps are provided and how the three studies individually and collectively address these research gaps are presented.

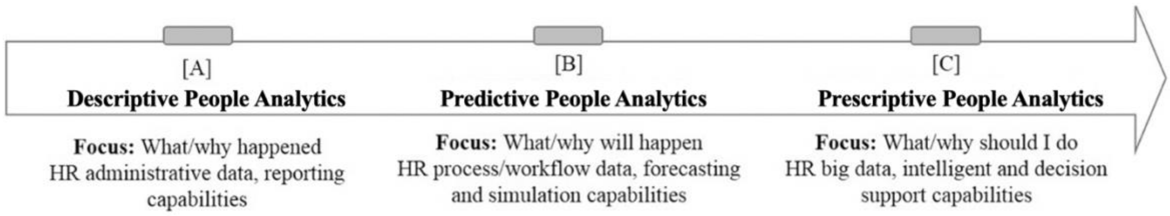
2.2 People Analytics: Definition

As a result of the ongoing digital transformation, many HR departments have begun to engage with workforce data to make evidence-based decisions in areas such as recruitment and selection, performance measurement, diversity and inclusion, and workforce planning (Hamilton & Sodeman, 2020; Harris, Craig, & Light, 2011; Kane, 2015; Marler & Boudreau, 2017; Rasmussen & Ulrich, 2015; Tursunbayeva, Pagliari, Di Lauro, & Antonelli, 2021). This application of using workforce data to improve decision making has been synonymously referred to by scholars as people analytics (Green, 2017; Kane, 2015; Nielsen & McCullough, 2018; Peeters et al., 2020; Tursunbayeva et al., 2018), talent analytics (Harris et al., 2011; Sivathanu & Pillai, 2020), human capital analytics (Andersen, 2017; Boudreau & Cascio, 2017; Levenson & Fink, 2017; Minbaeva, 2018), workforce analytics (Huselid, 2018; Simón & Ferreiro, 2018), and HR analytics (Angrave et al., 2016; Aral, Brynjolfsson, & Wu, 2012; Marler & Boudreau, 2017; McCartney et al., 2020; Rasmussen & Ulrich, 2015).

Consequently, these different terms have led to a constantly evolving conceptual definition among scholars, as evidenced in recent reviews conducted by Fernandez and Gallardo-Gallardo (2020) and Margherita (2020), who summarize numerous definitions currently found in the extant literature. For example, Marler and Boudreau (2017, p. 15) refer to HR analytics as *"[A]n 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".* Alternatively, Nielsen and McCullough (2018, p. 3) define people analytics as *"The use of data about human behaviour, relationships and traits to make business decisions and helps to replace decision-making based on anecdotal experience, hierarchy and risk-avoidance with higher-quality decisions based on data analysis, prediction and experimental research"*. Despite the differences among definitions, scholars can agree that people analytics is focused on evidence-based decision-making that combines data, analysis, and statistical modelling to improve and support strategic human capital and organizational decision-making.

In addition to these conceptualizations, various consulting firms and professional associations have added an additional layer to people analytics, claiming that it is not one dimensional but instead falls along a spectrum where the maturity of the people analytics function will determine the level of analytics that can be conducted (CIPD, 2019; Deloitte, 2013). For example, Deloitte (2013) claims that people analytics can be classified into four distinct levels; operational reporting, advanced reporting, advanced analytics, and predictive analytics. More recently, CIPD (2019) builds upon this premise, suggesting that people analytics operates on five levels: operational, descriptive, diagnostic, predictive, and prescriptive. This perspective has spread to the literature on people analytics, with scholars such as Margherita (2020) and Sivathanu and Pillai (2020) addressing the various levels of people analytics. According to Margherita (2020), people analytics follows a linear three-stage maturity model. At its lowest level, "descriptive", people analytics is focused on answering questions concerning what has happened. Next, the "predictive" stage focuses on what might happen in the future and why. Lastly, the "prescriptive" stage centres on determining what actions should be taken in response to the analysis.

Figure 2.1 Stages of People Analytics Maturity



Source: Margherita (2020, p.3)

Considering the various viewpoints and drawing upon several definitions from the extant literature, people analytics in this dissertation is defined as a progressive practice of transforming and translating workforce data into organizational insights, enabling managers to make informed and data-driven workforce decisions. This definition extends the previous definitions found in the people analytics literature by offering a holistic perspective of the concept considering the people analytics process from the start (incorporating the translation and transformation of data) to finish (generating organizational insights). In addition, this definition addresses the various levels and situational aspects of people analytics maturity, where organizations at the low end of maturity report on descriptive statistics, whereas organizations at the highest and most mature level of people analytics utilize AI and ML to analyze workforce data to perform predictive and prescriptive analytics.

2.3 Driving Forces of People Analytics

2.3.1 Theoretical Development in People Analytics

People analytics research to date has primarily focused on the application of people analytics in practice rather than exploring the phenomenon from a theoretical perspective (Marler & Boudreau, 2017; Minbaeva, 2017, 2018). However, three existing theories spanning the strategic human resource management and human capital literature are driving theory development in people analytics. First, strategic human capital theory (Becker, 1964) argues that individual employee KSAOs can be leveraged to generate sustainable competitive advantage. This indicates that people need to have the right KSAOs to conduct people analytics effectively. Second, RBV (Barney, 1991) suggests that resources that are valuable, rare, difficult to imitate, and are non-substitutable lead to competitive advantage. In this case, data, information and insights generated from people analytics constitute such a resource for organizations. Third, EBM (Rousseau, 2006) claims management decisions should be based on the combination of critical thinking coupled with the best sources of evidence taken from varied sources of information. EBM can be used to explain how people analytics can contribute to firm performance. This section outlines these fundamental theories that underpin the dissertation and situates them within the context of people analytics.

2.3.4.1 Strategic Human Capital Theory

Strategic human capital theory suggests that individual employee KSAOs can be leveraged to generate sustainable competitive advantage (Crook, Todd, Combs, Woehr, & Ketchen, 2011; Delery & Roumpi, 2017; Hitt, Bierman, Shimizu, & Kochhar, 2001; Wright, Coff, & Moliterno, 2014). There has been longstanding evidence supporting this relationship between human capital and performance. For example, in a meta-analysis of 66 studies conducted between 1995 and 2009, Crook, Todd, Combs, Woehr, and Ketchen (2011) found that human capital was positively associated with performance ($r = .17$ $p < .01$). More recently, the strategic human capital literature has shifted to focusing on how human capital resources or individual KSAOs are independently able to improve performance and generate sustainable competitive advantage (Barney & Felin, 2013; Crocker & Eckardt, 2014; Nyberg, Moliterno, Hale, & Lepak, 2014; Ployhart & Cragun, 2017; Ployhart & Moliterno, 2011; Ployhart, Nyberg, Reilly, & Maltarich, 2014). In addition to the linear effect of human capital inputs on value creation, human capital resource scholars have begun to theorize that human capital resource complementarities can occur when different human capital inputs (i.e. KSAOs) combine interactively to produce greater value together than apart (Adegbesan, 2009; Brymer & Hitt, 2019; Ployhart & Cragun, 2017; Ployhart et al., 2014).

Within the context of the people analytics literature, scholars have suggested that the KSAOs of HR Analysts are unique and can generate competitive advantage (Andersen, 2017; McCartney et al., 2020). For example, researchers have suggested that having high levels of analytical and storytelling ability allow for people analytics to add value to organizations (Andersen, 2017; Kryscynski et al., 2018; McCartney et al., 2020; McIver et al., 2018; van der Togt & Rasmussen, 2017). For instance, HR professionals with strong analytical ability have been found to result in higher levels of job performance (Kryscynski et al., 2018). Scholars have also argued that both storytelling and analytical skills are critical in enabling HR departments to make evidence-based decisions leading to improved departmental performance (Andersen, 2017; McCartney et al., 2020; McIver et al., 2018; Minbaeva, 2018; Peeters et al., 2020). Therefore, applying the principles of strategic human capital theory to people analytics suggests that individual KSAOs of HR Analysts can be leveraged to generate sustainable competitive advantage.

2.3.2.2 Resource-based View of the Firm

RBV (Barney, 1991) has become one of the most cited and influential theories in the strategic human resource management literature (Newbert, 2007; Wright, Dunford, & Snell, 2001; Wright & Ulrich, 2017). According to RBV, competitive advantage is derived from resources found within organizations that can be characterized as valuable, rare, difficult to imitate, and are non-substitutable (Barney, 1991; Wright, Dunford, & Snell, 2001; Sirmon, Hitt, Ireland, & Gilbert, 2011; Sirmon, Hitt, & Ireland, 2007). According to Barney (1991), resources considered valuable allow organizations to implement strategies intended to improve internal or external value, whereas rare resources are scarce and are not readily available. Furthermore, resources difficult to imitate cannot be easily acquired or developed by competitors, and non-substitutable resources cannot be switched to an alternative resource with the same value (Barney, 1991).

Applying RBV to people analytics, several parallels can be drawn and have been indirectly implied by scholars (Marler & Boudreau, 2017). For example, researchers and practitioners have discussed the value offered by people analytics through its ability to allow HR to identify and address workforce challenges (Huselid, 2018; Kryscynski et al., 2018; Marler & Boudreau, 2017; McIver et al., 2018; Minbaeva, 2018). In addition, the people analytics literature has also referred to the rarity of high-quality people analytics programs suggesting that many organizations struggle to utilize workforce data only offering basic reporting and descriptive statistics (Andersen, 2017; Angrave et al., 2016; Green, 2017; King, 2016; Levenson & Fink, 2017; Minbaeva, 2018). As such, effective people analytics programs are rare at present. Concerning the imitability of people analytics, according to Minbaeva (2018), to utilize and conduct value-adding people analytics, organizations need to have high-quality data, analytical capabilities, and the strategic ability to act. However, it is difficult for HR departments to have all three elements given the low levels of technology, poor data quality, few resources, lack of analytical competencies, and a lack of buy-in from senior management (Andersen, 2017). Finally, people analytics is its own stand-alone practice, meaning no available alternatives or substitutes can gain similar insights (Falletta & Combs, 2020). Taken collectively, people analytics meets the requirements set out by RBV, suggesting that people analytics given the data, information, and insight it creates, is a valuable resource for organizations with the potential to generate competitive advantage.

2.3.3.3 Evidence-based Management

Evidence-based practice originated within the health care profession to better use scientific research to inform decision-making concerning patient care (Baba & HakemZadeh, 2012; Briggs & McBeath, 2009; HakemZadeh & Baba, 2016; Pfeffer & Sutton, 2006; Walshe

& Rundall, 2001). Over the past few decades, the idea of incorporating both research and practical experience has transcended various disciplines, including HRM (Briggs & McBeath, 2009; Coron, 2021; Walshe & Rundall, 2001). The core argument of EBM is that management decisions should be based on the combination of critical thinking coupled with the best sources of evidence taken from four sources of information (Rousseau & Barends, 2011). These four sources include scientific evidence found in peer-reviewed academic papers, organizational facts such as metrics and analytics, professional experience and judgment, and considering the outcome on affected stakeholders (Bezzina et al., 2017; Cassar & Bezzina, 2017; Rousseau, 2006; Rousseau & Barends, 2011).

According to Barends, Rousseau and Briner (2014), EBM comprises of six activities, including asking, acquiring, appraising, aggregating, applying, and assessing. For example, organizations must translate an issue or problem into an answerable question (asking), systematically search for and retrieve the best available evidence (acquiring), critically judge the trustworthiness and relevance of the evidence (appraising), weigh and pull together the evidence (aggregating), incorporate the evidence into the decision-making process (applying), and evaluate the outcome of the decision (assessing).

From a people analytics standpoint, EBM has been cited as one factor that can contribute to improving overall managerial decisions (Coron, 2021; Falletta, 2014; Falletta & Combs, 2020; Ferraris, Mazzoleni, Devalle, & Couturier, 2019; Greasley & Thomas, 2020; Ulrich & Dulebohn, 2015; van der Togt & Rasmussen, 2017; Wolfe, Wright, & Smart, 2006). For instance, according to Coron (2021), evidence-based human resource management relies on using people data and metrics to increase knowledge and, in turn, improve HR decision-making. Similarly, according to van der Togt and Rasmussen (2017), it is the individual experience, beliefs, intuition, and facts acquired through people analytics that serves as another source of evidence HR professionals can use to enhanced decision-making capabilities and better organizational results. As such, this dissertation posits that people analytics is one of the four sources of evidence that offers HR managers and executives actionable insights and organizational knowledge in the form of statistical analysis, scorecards, and visualizations on various HR activities.

2.3.2 Technology Development and Management

The rapid advancement of information technology in recent years has sparked a digital revolution, with organizations taking advantage of big data to address previously unknown opportunities (Dubey et al., 2019; Fosso Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015; Kim, Wang, & Boon, 2021; Wamba et al., 2017). As a result, research surrounding the topic of big data and its applications has seen increasing attention from scholars and professionals with the aim to understand how data can be transformed into actionable insights leading to improved organizational performance (Chierici, Mazzucchelli, Garcia-Perez, & Vrontis, 2019; Ferraris et al., 2019; Santoro, Fiano, Bertoldi, & Ciampi, 2019; Singh & Del Giudice, 2019).

This digital transformation and interest in applying big data have transcended various management disciplines, including HRM, with HR departments becoming more digital through the implementation of electronic HRM (e-HRM) technologies over the past two decades (Kim et al., 2021; Parry & Tyson, 2011; Stone, Deadrick, Lukaszewski, & Johnson, 2015a; Strohmeier, 2020; Strohmeier & Kabst, 2014; Zhou, Liu, Chang, & Wang, 2021). This transition and shift toward a more technology-enabled HR department have resulted in the concept of HRM digitalization, which refers to the use of digital technology and related data to enhance the efficiency and effectiveness of HRM practices (Zhou et al., 2021). Furthermore, the shift to making evidence-based decisions through technologies like AI and ML has heightened interest in people analytics (Cheng & Hackett, 2019; Falletta & Combs, 2020; Fernandez & Gallardo-Gallardo, 2020; Marler & Boudreau, 2017).

Evidence of this digitalization can be seen through the various HR practices that have benefited from technology and e-HRM (Kim et al., 2021; Stone et al., 2015; Strohmeier, 2007; Upadhyay & Khandelwal, 2018; Zhou et al., 2021). Two areas in particular that have seen the most prominent benefit have come in recruitment and selection and training and development (Kim et al., 2021). For example, the advent of e-recruitment coupled with AI technology has enabled HR departments to quickly and efficiently organize and evaluate job applications and has led to improved recruitment decisions (Black & van Esch, 2020; Boselli, Cesarini, Mercorio, & Mezzanzanica, 2018; El Ouirdi, El Ouirdi, Segers, & Pais, 2016; D. Grant & Newell, 2013; Lee, 2011). Likewise, with respect to e-learning, online training platforms have allowed for the effective training of employees using digital learning environments (Brown & Charlier, 2013; Giannakos, Mikalef, & Pappas, 2021). Moreover, technology coupled with people data has allowed HR departments to uncover areas of development for employees (Rasmussen & Ulrich, 2015).

Overall, the development of technology has been a driving force in the implementation and growth of people analytics enabling HR professionals to employ more data-driven decision-making (Ashbaugh & Miranda, 2002; Buttner & Tullar, 2018; Dulebohn & Johnson, 2013; Huselid, 2018; Marler & Boudreau, 2017; McIver et al., 2018; Schiemann, Seibert, & Blankenship, 2018; Stone & Deadrick, 2015; van der Togt & Rasmussen, 2017). Given the limited use of advanced forms of technology in organizations, this dissertation does not focus on these technologies. Instead, it concentrates on the KSAOs of HR Analysts and the adoption and performance impact of people analytics.

2.4 People Analytics: Applications

People analytics has seen significant interest among HR practitioners. Over 70% of HR departments identify people analytics as a high priority for their organizations (Leonardi & Contractor, 2019). This is evidenced by the increasing number of HR departments investing in human capital software and forming people analytics teams tasked with exploiting insights derived from employee data in areas such as recruitment and selection, employee engagement, diversity and inclusion, and retention and turnover (Baesens et al., 2017; Buttner & Tullar, 2018; Falletta & Combs, 2020; Harris et al., 2011; King, 2016; Minbaeva, 2018; Peeters et al., 2020; Sharma & Sharma, 2017; van der Togt & Rasmussen, 2017).

As expected, given this popularity, professional associations, including CIPD and consulting firms such as Deloitte, have begun to publish blogs; white papers; and reports targeted at a practitioner audience, claiming the benefits of leveraging people data to make decisions that are more informed and data-driven (CIPD & WorkDay, 2018; Deloitte, 2017, 2018). This practitioner-focused perspective has led to several case studies being published demonstrating how organizations are currently using people analytics to address HR and business challenges (Buttner & Tullar, 2018; Gelbard, Gonen, Carmeli, & Talyansky, 2018; Harris et al., 2011; Marler & Boudreau, 2017; McIver et al., 2018; Minbaeva, 2018; Rasmussen & Ulrich, 2015). For example, a recent case study conducted by Simón and Ferreiro (2018) describes the development and implementation of a people analytics program at Inditex, a large Spanish multinational fashion retail group. In collaboration with the authors, Inditex created a standard set of HR-specific questions and developed key performance indicators centred around workforce analytics. Doing so led HR Managers at Inditex to monitor and make more informed decisions around their workforce, resulting in higher overall store performance (Simón & Ferreiro, 2018).

Similarly, at Royal Dutch Shell, people analytics projects have been implemented to address topics such as: examining and identifying the drivers of individual and company performance, the extent that employee engagement impacted overall company safety, and what factors contribute to high employee engagement (van der Togt & Rasmussen, 2017). A third case demonstrated how Bank of America, working in collaboration with Humanyze, (a people analytics software provider) used people analytics to improve HR and business outcomes (Kane, 2015). Humanyze designed and developed ID badges for employees, adding microphones, Bluetooth, and infrared technology to facilitate the collection of workforce data (Kane, 2015). Although such technology is not prevalent in practice yet, organizations have begun to experiment and use these types of analytics to solve workforce challenges (Jeske & Calvard, 2020; Kane, 2015; Khan & Tang, 2017). In the Bank of America case, they implemented the ID badge in several call centres to address variations in call centre performance. Their findings determined that the way employees interacted with their coworkers was the most significant factor in predicting productivity (Kane, 2015). Table 2.1 summarizes 11 people analytics cases implemented by organizations aimed at improving various HR and business challenges.

2.5 Research Gaps in People Analytics Research and Three Studies

Over the past several years, people analytics has garnered significant interest among scholars. For example, a review conducted by Marler and Boudreau (2017) highlights 14 people analytics papers that were published in journals featured on the Journal Quality List (JQL) between 2005 and 2016. Since then, further reviews have been conducted by Tursunbayeva et al. (2018), Fernandez and Gallardo-Gallardo (2020), and Margherita (2020), all demonstrating the significant growth and interest in people analytics.

To date, studies surrounding people analytics have focused on the application of people analytics (Fernandez & Gallardo-Gallardo, 2020; Margherita, 2020; Marler & Boudreau, 2017). Moreover, several publications have begun to discuss the current limitations and challenges facing the development of people analytics (Boudreau & Cascio, 2017; Huselid, 2018; Jeske & Calvard, 2020; Levenson & Fink, 2017; Minbaeva, 2018), the best practices in developing and utilizing people analytics (Falletta & Combs, 2020; Green, 2017), and the impact and importance of analytical skills (Kryscynski et al., 2018; McCartney et al., 2020).

Table 2.1 Uses and Outcomes of People Analytics in Organizations

Study	Company	Problem Description	People Analytics Actions	Results
Harris, Craig, and Light (2011)	Google	Difficulty in identifying potential candidates who would perform well and succeed at Google through traditional techniques.	The people analytics team developed a more sophisticated approach to recruitment using biographical data, employee attitudes, behaviours, and personality data. With this information, the people analytics team matched candidate factors against a list of best predictors of performance and applied an algorithm that produced a score to predict the candidate's likelihood of success.	• Allowed Google to manage the rapid growth in Hiring (an increase of 38%). • The more analytical approach ensures that Google does not overlook potential employees.
Coco, Jamison, and Black (as cited in Marler and Boudreau, 2017)	Lowes	Employee engagement and store performance.	The HR department established a link between the HR process, employee engagement, and overall store performance using people analytics.	• Highly engaged workforce. • 4% higher average customer ticket sales per store.
Kane (2015)	Bank of America	Experiencing variance in call centre performance.	Implemented ID badges allowing for the collection of voice and movement pattern data.	• Identified that cohesive groups or employees who speak to 5 people at the company completed calls in half the time. • Implemented a new break schedule so that employees could speak to other coworkers. • Cohesion increased by 18%, stress reduced by 19%, and productivity increased by 23%

Mclver et al. (2018)	Foot Locker	Experiencing high levels of turnover in their retail stores.	Implemented analytics-driven technology platform and HRIS that focused on improving candidate selection, candidate experience, and employee onboarding.	• Double-digit reduction in employee turnover. • More employee time selling. • A double-digit increase in productivity. • Increased worker satisfaction. • Increase in-store sales.
Mclver et al. (2018)	Johnson Controls	Performance management review process.	The people analytics team analyzed the performance management review process in detail and discovered that not completing the goal-setting piece of the review was a strong indicator and predictor of controllable turnover.	• Shifted the performance management process to focus on frequent goal setting to reduce the risk of controllable turnover.
Minbaeva (2018)	Unnamed Organization	Difficulty convincing managers involved in talent management programs to relocate internationally.	The people analytics team analyzed and combined career relocation and movement, promotion, and salary data over a 10-year period.	• Discovered that international relocation had a positive and significant correlation with future promotions, with the probability of promotion at 10%
Minbaeva (2018)	Unnamed Organization	A significant variance in the performance of 16 independent profit centres across the organization.	Using qualitative and quantitative methods, the people analytics team examined several factors such as organizational design, organizational culture, and external factors to determine the cause of the variance.	• Developed a “People Index” which accounted for 60% of the variance between profit centres. • Developed a Toolkit around the People Index for developing high-performing teams.
Rasumssen and Ulrich (2015)	Maersk Drilling	Struggling to recruit lead specialist positions due to market talent shortage and organizational growth.	Used people analytics to identify that the company graduate trainee program yielded the necessary talent.	• Doubled recruitment to the graduate trainee program to facilitate growth and training for hard-to-fill roles.

Rasumssen and Ulrich (2015)	Maersk Drilling	Experiencing substantial variance between rig performance while trying to grow by 40% over a 4-year period.	Used people analytics and business analytics, which identified a strong relationship between leadership quality, crew competence, safety performance, operational performance, and customer satisfaction.	• Findings were integrated into a complete value chain analysis and scorecards to communicate with internal and external stakeholders.
Simón and Ferreiro (2018)	Inditex	Rapid international growth was lacking the competencies to make predictions about the contribution of their workforce to store performance.	Created a standard set of HR-specific questions and develop key performance indicators all centred around workforce analytics.	• led to HR Managers at Inditex being able to monitor and make more informed decisions around their workforce, resulting in higher overall store performance
Peeters, Paauwe, and Van De Voorde (2020)	ING	ING needed to recruit several specialists to work on their "Know Your Customer" team. However, it is challenging to acquire talent with the necessary skills.	The people analytics team matched 9000 internal job titles to an external database offering a complete overview of the employee populations knowledge, skills, abilities, and other characteristics (KSAO's).	• The data allowed ING to successfully identify current employees who possessed the required KSAO's to fill these critical roles. • Offered development opportunities to employees.

Despite these advances, research in people analytics is still in its infancy, with several gaps that remain unexplored within the current literature. This dissertation focuses on three research gaps currently evolving within the people analytics literature. First, is the lack of systematic investigation of the debates and challenges faced by people analytics. Second, the KSAOs required to influence people analytics are unestablished. Third, the unknown performance impact of people analytics. Each gap is addressed below and followed by a discussion on how the studies address the research gaps.

2.5.1 Lack of Systematic Investigation of the Debates and Challenges in People Analytics

With recent advancements in information technology, people analytics has become an emerging trend in HRM (Falletta & Combs, 2020; Huselid, 2018; Margherita, 2020; Marler & Boudreau, 2017). Despite the significant growth of people analytics literature and the continued adoption of people analytics in practice, the challenges and emerging debates attributed to the adoption of people analytics is widespread in the existing people analytics literature. For example, many scholars have found inconsistencies surrounding what constitutes people analytics, given the various terms used synonymously to describe the concept of people analytics (Ben-Gal, 2019; Huselid, 2018; Levenson & Fink, 2017; Marler & Boudreau, 2017; McIver et al., 2018; Tursunbayeva et al., 2018; van den Heuvel & Bondarouk, 2017). Furthermore, although many organizations claim the benefits of people analytics, lack of evidence demonstrating the success of people analytics has caused scholars to become more skeptical, questioning the legitimacy of the concept (Andersen, 2017; Angrave et al., 2016; Baesens et al., 2017; Levenson & Fink, 2017; Marler & Boudreau, 2017; McIver et al., 2018; Rasmussen & Ulrich, 2015).

These two examples highlight inconsistencies found within the people analytics literature and illustrate the emerging research gap brought on by the increased interest and adoption of people analytics. To address this important research gap and take stock of the quickly evolving field of research, Study 1 aims to answer the research question of what debates and challenges are emerging as a result of people analytics adoption. In response to this question, Study 1 conducts a systematic literature review of peer-reviewed articles focused on people analytics published in ABS ranked journals between 2011 and 2020.

2.5.2 Unestablished KSAOs Required to Influence People Analytics

Research investigating the underlying mechanisms and antecedents that facilitate people analytics performance at the individual level remains a significant gap within the existing people analytics literature (Ellmer & Reichel, 2021; McCartney et al., 2020; Minbaeva, 2018). This is evidenced by several scholars who have called for more research to investigate and understand the underlying mechanisms facilitating people analytics. For example, Minbaeva (2018) suggests that future research is needed to discover the necessary causal mechanisms and factors that link people analytics to performance. Further, Peeters et al. (2020) called for research to examine how the various elements of their people analytics effectiveness wheel, including the individual KSAOs of team members, facilitate people analytics performance given the current lack of evidence demonstrating how this occurs.

In a similar vein, micro researchers in people analytics have also highlighted that despite the increase in scholarly work focused on the individual KSAOs required to perform people analytics, what remains unclear are which KSAOs are most influential to people analytics success (Andersen, 2017; Ellmer & Reichel, 2021; Huselid, 2018; McCartney et al., 2020; McIver et al., 2018; Minbaeva, 2018; Peeters et al., 2020). Moreover, despite the growing number of case studies and qualitative research projects identifying analytical and storytelling skills as the two broad human capital inputs required for people analytics, the direct impact of these skills on enhancing people analytics performance remains unknown (Andersen, 2017; Huselid, 2018; McCartney et al., 2020; McIver et al., 2018; Minbaeva, 2018; Peeters et al., 2020). To address this gap, Study 2 aims to answer the research question of what factors contribute to the success of people analytics. By doing so, the study uncovers how analytical and storytelling skills, two valuable types of human capital, independently and collectively lead to higher levels of people analytics performance. Moreover, the study extends the current understanding of the direct and complementarity impact of human capital on performance.

2.5.3 Unknown Performance Impact of People Analytics

Despite a rise in published case studies, blogs, and white papers discussing the performance impact of people analytics, academics have become more hesitant, challenging whether HR departments should invest in people analytics (Andersen, 2017; Angrave et al., 2016; Baesens et al., 2017; Levenson & Fink, 2017; Marler & Boudreau, 2017; McIver et al., 2018; Rasmussen & Ulrich, 2015). These criticisms have emerged due to the lack of evidence supporting the success of people analytics and its impact on strategic decision-making. For example, according to Marler and Boudreau (2017), although several publications emphasize the innovation of people analytics, few scientific studies currently support the performance impact of people analytics. Likewise, according to McIver et al. (2018), despite great enthusiasm for adopting people analytics in practice, there remains a misunderstanding of how organizations can leverage and use people analytics to increase organizational performance.

As can be seen, although many HR departments are investing in people analytics, success stories demonstrating its effects on performance are rare, with claims based more on belief than academic research (Baesens et al., 2017; Rasmussen & Ulrich, 2015). Study 3 aims to answer the research question of how does people analytics impact organizational performance. To address this important research gap, this study theorizes that people analytics positively impacts organizational performance through its EBM capability and its HR technology. Overall, this study offers insight into why, how, and when people analytics leads to increased organizational performance.

2.6 Summary

This chapter focused on offering a broad overview of the core topics featured in the dissertation. First, the concept of people analytics was introduced. Second, the driving forces in theory and technology shaping the adoption and implementation of people analytics were presented. In particular, the three fundamental theories that underpin the dissertation and the ongoing digital transformation of HRM including RBV, EBM, and strategic human capital theory. Next, applications and examples of people analytics were discussed, offering insight into how HR departments have used people analytics to make evidence-based decisions. Finally, the research gaps addressed by the dissertation were reviewed and how the three studies were designed to individually and collectively address these research gaps were presented. The three studies will be presented in detail in Chapters 3 to 5.

CHAPTER 3 STUDY 1 – PROMISE VS. REALITY: ONGOING DEBATES IN PEOPLE ANALYTICS

3.1 Abstract

Purpose – Despite the significant growth of people analytics literature and the continued adoption of people analytics in practice, the challenges and emerging debates attributed to the adoption of people analytics is underdeveloped in the existing people analytics literature. Accordingly, this study aims to address the research question of what debates and challenges are emerging as a result of people analytics adoption.

Design/methodology/approach – This study conducts a systematic literature review of peer-reviewed articles focused on people analytics published in ABS ranked journals between 2011 and 2020.

Findings – The review illustrates and critically evaluates several emerging debates and issues faced by people analytics, including inconsistency among the concept and definition of people analytics, people analytics ownership, ethical and privacy concerns of using people analytics, missing evidence of people analytics impact, and readiness to perform people analytics.

Practical implications – This review presents a comprehensive research agenda demonstrating the need for collaboration between scholars and practitioners to successfully align the promise and the current reality of people analytics.

Originality/value – This systematic review is distinct from existing reviews in three ways. First, this review synthesizes and critically evaluates the significant growth of peer-reviewed articles focused on people analytics published in ABS-ranked journals between 2011 and 2020. Second, the study adopts a thematic analysis and coding process to identify the emerging themes in the existing people analytics literature, ensuring the comprehensiveness of the review. Third, this study focuses and expands upon the debates and issues evolving within the

emerging field of people analytics and offers an updated agenda for the future of people analytics research.

Keywords: *People Analytics, HR Analytics, Workforce Analytics, Human Resource Management, Systematic Literature Review*

3.2 Introduction

People analytics has recently become an emerging trend within the field of HRM (Ben-Gal, 2019; CIPD & WorkDay, 2018; Huselid, 2018; King, 2016; Kryscynski et al., 2018; Marler & Boudreau, 2017; McIver et al., 2018; Tursunbayeva et al., 2018; van den Heuvel & Bondarouk, 2017). However, people analytics is not entirely new. Despite its recent increase in popularity and significant growth and adoption within organizations, people analytics can be traced back to the scientific management movement pioneered by Fredrick Taylor in the early 20th century (Schiemann et al., 2018).

Several decades later, the digitalization of HR led by recent advancements in information technology such as human resource information systems (HRIS), AI, and ML, has presented HR professionals with the opportunity to collect and analyze large volumes of workforce data (Ashbaugh & Miranda, 2002; Baldry, 2011; Buttner & Tullar, 2018; CIPD & WorkDay, 2018; Dulebohn & Johnson, 2013; Huselid, 2018; Marler & Boudreau, 2017; McIver et al., 2018; Schiemann et al., 2018; Stone & Deadrick, 2015; van der Togt & Rasmussen, 2017). By doing so, people analytics has become more attractive and accessible to organizations garnering significant interest among scholars and practitioners (Greasley & Thomas, 2020). For instance, in a review conducted by Marler and Boudreau (2017), 14 people analytics papers were published in journals featured on the Journal Quality List (JQL) between 2005 and 2016. Since then, the number of articles dedicated to people analytics has tripled, aided by two special issues devoted to people analytics in ABS ranked journals. One in the *Journal of Organizational Effectiveness: People and Performance* (2017: Volume 4, Issue 2, edited by Dana Minbaeva) and the second in *Human Resource Management* (2018: Volume 57, Issue 3, edited by Mark Huselid).

Meanwhile, in practice, organizations are leveraging workforce data to make strategic workforce decisions (Andersen, 2017; Cheng & Hackett, 2019; Deloitte, 2017, 2018; Levenson, 2018; Minbaeva, 2018; Rasmussen & Ulrich, 2015; Stone & Deadrick, 2015; van der Togt & Rasmussen, 2017). To do so, the assembling of people analytics teams comprised of members with a diverse range of skills has become an increasingly popular way for HR functions to streamline, leverage, and utilize the vast amounts of workforce data accessible to make strategic HR decisions (Andersen, 2017; Fernandez & Gallardo-Gallardo, 2020; McIver et al., 2018; Peeters et al., 2020). For example, analytics service providers such as Humanyze have begun working with organizations implementing ID badges equipped with motion sensors, microphones, and Bluetooth technologies, allowing for organizations to monitor employees and collect real-time data used by people analytics teams to make data-driven decisions on staffing and engagement (Kane, 2015). Likewise, the people analytics team at Google has developed an analytical approach to their recruitment process, applying predictive analytics to calculate a candidates likelihood of success using biographical data, personality data, and employee attitudes (Harris et al., 2011).

Despite the significant growth of people analytics literature and the continued adoption of people analytics in practice, the challenges and emerging debates attributed to the adoption of people analytics is underdeveloped in the existing people analytics literature. Accordingly, this study aims to address the research question of what debates and challenges are emerging as a result of people analytics adoption? In response to this question, this study conducts a systematic literature review of peer-reviewed articles focused on people analytics published in ABS ranked journals between 2011 and 2020. To do so, this study adopts a thematic analysis approach to systematically and critically evaluate the people analytics articles. This review finds several themes illustrating numerous debates and emerging challenges within the people analytics literature. Lastly, the study sets an agenda for future research by proposing seven research areas critical to narrowing the gap created by these debates and shaping the future of research in people analytics.

This systematic review is distinct from existing reviews conducted by Marler and Boudreau (2017) and Tursunbayeva, Di Lauro and Pagliari (2018) in three ways. First, this review synthesizes and critically evaluates the significant growth of peer-reviewed articles focused on people analytics published in ABS ranked journals between 2011 and 2020. Second, the study adopts a thematic analysis and coding process to identify the emerging themes in the existing people analytics literature, ensuring the comprehensiveness of the review. Third, this study focuses and expands upon the debates and issues evolving within the emerging field of people analytics and offers an updated agenda for the future of people analytics research.

The subsequent sections of this paper are organized as follows: First, the methodology section will outline the search process, including the rationale for the databases referenced, the keywords identified, and the criteria used in selecting the appropriate articles. Additionally, the methodology section offers an evaluation of the selected articles, along with a description of the coding process. Second, the research findings section will present the themes associated with the debates and challenges emerging as a result of people analytics adoption. Lastly, the discussion and conclusion section will critically evaluate each of the topics mentioned above and set out an agenda for future research in people analytics.

3.3 Methodology

3.3.1 Literature Search

The literature search began with sourcing academic and peer-reviewed journal articles from five databases: ABI/Inform, Business Source Complete, Emerald, SCOPUS, and the Wiley Online Library. Each database was selected due to its comprehensive range of peer-reviewed articles and access to leading management journals. Additionally, both Business Source Complete and SCOPUS were included to maintain consistency with the databases used by Marler and Boudreau (2017) in their evidence-based review.

The following key search terms were used to identify and select articles for inclusion: “Workforce Analytics”; “HR Analytics”; “Human Resource Analytics”; “People Analytics”; “Human Capital Analytics”. Each search term was selected as they have been used synonymously in practice and in the academic literature to refer to people analytics (Ben-Gal, 2019; Huselid, 2018; McIver et al., 2018; Tursunbayeva et al., 2018; van den Heuvel & Bondarouk, 2017). The result of the initial literature search yielded 2,721 articles and studies between the five databases. Table 3.1 summarizes the distribution of results from different databases.

Table 3.1 Results from Initial Literature Search

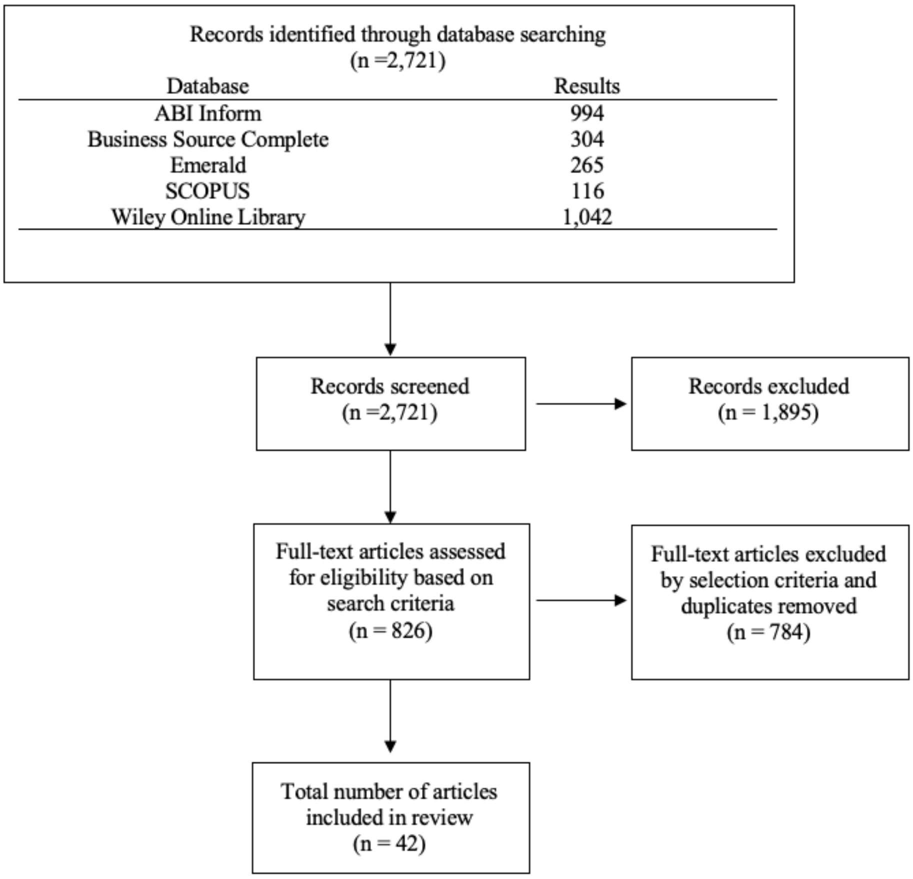
Journal	Results from Literature Search
ABI/Inform	994
Business Source Complete	304
Emerald	265
SCOPUS	116
Wiley Online Library	1,042
In total	2721
Full-Text articles assessed for eligibility	826*

Note: * The number was reduced from 2721 to 826 due to 1,895 of the 2,721 results not being peer-reviewed.

3.3.2 Selection Process and Screening Criteria

After conducting the initial literature search, the 2,721 articles and studies were transferred into an excel spreadsheet and organized using 11 categories: database, author(s), article title, year published, journal title, volume number, issue number, peer-review, journal field, ABS ranking, and abstract. As a result, 1,895 of the 2,721 results were excluded due to not being peer-reviewed articles, resulting in 826 journal articles remaining. Next, the remaining journal articles were screened using three selection and inclusion criteria: (1) journals must appear on the ABS journal rankings, (2) articles must be published in an English language journal, and (3) articles are published between the years between 2011 and 2020. The years 2011 and 2020 were chosen due to the first people analytics paper being published in an ABS-ranked journal in 2011 (Marler and Boudreau, 2017). Articles were also screened based on their perceived relevance to people analytics through their title and abstract. After removing all duplicate journal articles (784), 42 articles were identified as relevant for the review. Figure 3.1 outlines the systematic approach taken concerning the literature search.

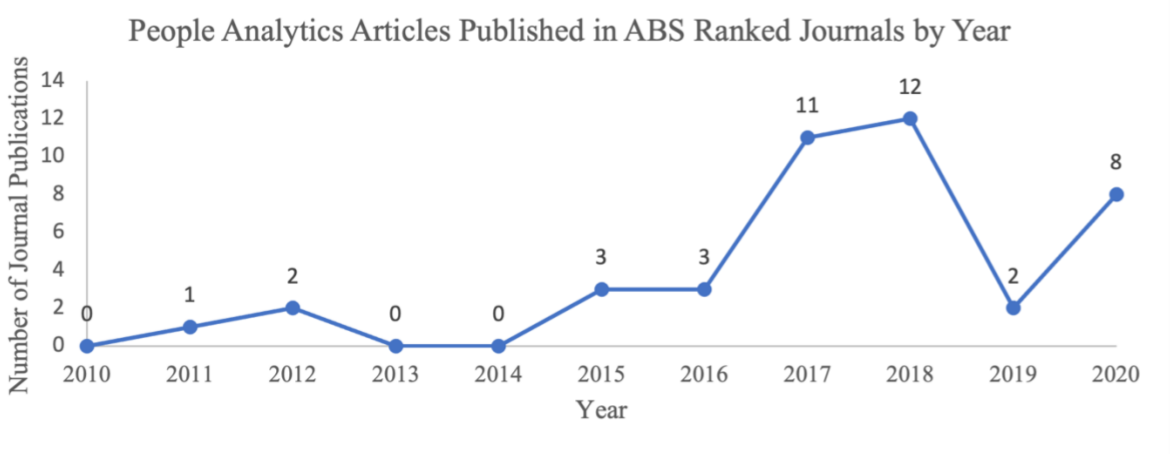
Figure 3.1. Literature Searching Process for People Analytics Publications



3.3.3 Evaluation of Selected Articles

The 42 articles identified through the literature search demonstrate the significant increase in academic publications and interest in people analytics since 2011, with many articles being published within the past few years. For example, of the 42 articles identified as relevant for this review, 33 were published between 2017 and 2020. Figure 3.2 highlights the increase of people analytics publications in ABS ranked journals from 2011 – 2020.

Figure 3.2 People Analytics Publications 2011 - 2020



In terms of journal distribution, the articles identified through the literature search represent 26 distinct academic journals, demonstrating the wide array of journals currently accepting people analytics research. Table 3.2 shows the ABS ranked journal distribution of published people analytics articles.

The majority of recent research offers much-needed insight into the development of people analytics by focusing on the current limitations and challenges facing the development of people analytics (Andersen, 2017; Boudreau & Cascio, 2017; Huselid, 2018; Jeske & Calvard, 2020; Levenson & Fink, 2017; Minbaeva, 2018; van der Togt & Rasmussen, 2017), best practices in utilizing people analytics (Green, 2017; Peeters et al., 2020), the impact and importance of analytical skills (Andersen, 2017; Kryscynski et al., 2018; McCartney et al., 2020; McIver et al., 2018; Minbaeva, 2018; Vargas, Yurova, Ruppel, Cynthia, Tworoger, & Greenwood, 2018), and the potential future applications of people analytics by drawing upon practitioner experience and case studies (Minbaeva, 2018; Schiemann et al., 2018; Simón & Ferreiro, 2018; van den Heuvel & Bondarouk, 2017; van der Togt & Rasmussen, 2017). A summary of the 42 articles included in the review can be found in appendix A.

Table 3.2 Journal Distribution in Publishing People Analytics Articles

Journal Title	Number of Articles Published	Journal Ranking (ABS)
Management Science	1	4*
Human Resource Management	6	4
European Journal of Operational Research	1	4
Human Resource Management Journal	2	4
Decision Support Systems	1	3
Harvard Business Review	1	3
Human Resource Management Review	1	3
International Journal of Human Resource Management	2	3
MIT Sloan Management Review	2	3
Business Horizons	1	2
Employee Relations	1	2
Expert Systems: The Journal of Knowledge Engineering	1	2
Human Resource Development Review	1	2
International Journal of Information Management	1	2
Journal of Forecasting	1	2
Journal of General Management	1	2
Journal of Organizational Effectiveness: People and Performance	8	2
Personnel Review	2	2
Organizational Dynamics	1	2
Competitiveness Review	1	1
Equality, Diversity, and Inclusion: An International Journal	1	1
International Journal of Organizational Analysis	1	1
Journal of Business Strategy	1	1
Kybernetes	1	1
Management Research Review	1	1
Journal of Work-Applied Management	1	1
Total of Published Articles	42	

3.3.4 Literature Review and Coding Method

A thematic analysis was conducted using the 42 articles to ascertain the underlying themes, trends, and recent developments in the people analytics literature. Thematic analysis was the chosen method to identify and classify themes and patterns using a systematic coding process (Boyatzis, 1998; Braun & Clarke, 2006; Ibrahim, 2012). Similarly, performing a thematic analysis can provide a high degree of detail and help interpret many aspects of the research question or research topic (Braun & Clarke, 2006). To conduct the thematic analysis, NVivo, a text analysis software program, was used. The 42 articles were loaded into a new NVivo project for analysis. Each paper was read to understand the selected articles, and subsequent nodes were created, identifying potential themes. Codes were then generated based on keywords and statements found within each of the 42 articles. Once all codes had been identified, they were grouped into clearly defined themes related to the research question.

3.4 Research Findings

The prevalence and growth of people analytics literature coupled with organizations implementing and adopting people analytics to make strategic workforce decisions have given rise to several debates and issues currently being faced by HR and business professionals. These emerging debates and issues centre around five major themes, including (1) the inconsistency among the concept and definition of people analytics, (2) people analytics ownership debate, (3) ethical and privacy concerns of using people analytics, (4) missing evidence of people analytics impact, and (5) readiness to perform people analytics. Table 3.3 demonstrates the five themes identified as part of the research question and presents quotes from the journal articles. Each debate and issue are discussed below.

3.4.1 Inconsistency Among the Concept and Definitions of People Analytics

Despite its popularity, a clear definition of people analytics has yet to be established among scholars and professionals due in part to the various terms used synonymously to describe the concept of people analytics (Ben-Gal, 2019; Huselid, 2018; Levenson & Fink, 2017; Marler & Boudreau, 2017; McIver et al., 2018; Tursunbayeva et al., 2018; van den Heuvel & Bondarouk, 2017). One example is the term HR metrics, which has been used synonymously with people analytics, despite being a very different and distinct concept.

Table 3.3 Quotes and Subthemes for the Debates and Issues of People Analytics Adoption

Illustrative Quotes	Subtheme
"In addition to Workforce Analytics, the terms HR Metrics, HR Analytics, Talent Analytics, Human Capital Analytics, and People Analytics have all been used to describe this field". (Huselid, 2018, p. 680)	Inconsistency Among the Concept and Definition of People Analytics
"Take HR analytics out of HR. This may sound drastic, but when HR analytics matures, it initially starts cooperating more with other departments' teams (in finance, operations, etc.), and eventually becomes part of cross functional/end-to-end analytics — looking at human capital elements in the entire value-chain". (Rasmussen & Ulrich, 2015, p. 238)	People Analytics Ownership Debate
"Company-collected relational data, however, creates new challenges. Although most employment contracts give firms the right to record and monitor activities conducted on company systems, some employees feel that the passive collection of relational data is an invasion of privacy". (Leonardi and Contractor, 2019, p. 15)	Ethical and Privacy Concerns of Using People Analytics
"Despite the promise, successful strategic HR analytics projects appear to be few and far between. Although many organizations have begun to engage with HR data and analytics, most have not progressed beyond operational reporting". (Angrave et al., 2016, p.4)	Missing Evidence of People Analytics Impact
"Success with human capital analytics will depend, in large part, on HR's ability to find and nurture analytical talent – the people who produce the data, the quantitative analysis, and statistical models you need to make better decisions and achieve better results. Connecting these specialists with the business will ensure that they understand how human capital analytics can drive value for the business". (Harris et al., 2011, p. 11)	Readiness to Perform People Analytics

For instance, according to van den Heuvel and Bondarouk (2017), *"Given that HR analytics explicitly involves linking people characteristics, HR practices or policies, and business outcomes, the analytics concept is distinct and the term should not be used interchangeably with the term metrics"* (p. 131).

Moreover, van den Heuvel and Bondarouk (2017) suggest that a key differentiator between the two concepts is that *"metrics do not provide a robust insight into why something* *occurred, what explains differences in outcomes, or what the likelihood is that an event will reoccur in the future"* (p. 131).

Accordingly, scholars have begun to propose several definitions and descriptions to illustrate and add clarity around the concept of people analytics. However, rather than adding clarity, this practice has highlighted several inconsistencies surrounding the concept of people analytics.

For example, Marler and Boudreau (2017) suggest that people analytics can be defined as "[*a]n 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*" (p. 15).

In contrast, Huselid (2018) defines people analytics as "*The process involved in understanding, qualifying, managing, and improving the role of talent in the execution of strategy and creation of value. It included not only a focus on metrics (e.g. what do we need to measure about our workforce?) but also analytics (e.g. how do we manage and improve the metrics we deem to be critical for business success)*" (p.680).

Table 3.4 below summarizes the varying definitions and the terms associated with people analytics. It is evident that there are several inconsistencies between how scholars and practitioners view, label, and define people analytics. Together, however, they agree that people analytics involves using workforce data to help make better decisions, which can occur at various maturity levels. As such, people analytics should be seen as situational, falling along a spectrum where organizations at the low end of maturity report on descriptive statistics. In contrast, organizations at the highest and most mature level of people analytics utilize AI and ML to analyze workforce data to perform predictive and prescriptive analytics.

Table 3.4 Various Definitions of People Analytics

Terms	Definition	Key Features	Study
HR analytics	*involves complex multistage* ***projects*** *requiring question formulation, research design, data organization, and* ***statistical and econometric modelling*** *of different levels of complexity and rigor that acts as a guide to future management action.*	• Decision-making process • Data • Statistics/modeling	Angrave et al. (2016)
HR analytics	*refers to a too-wide array of measurement and analytical* ***approaches****. It is distinct from HR reporting as it focuses much more on the impact of HR programs and processes - addressing more of the "so what?" questions including ROI.*	• Process to address impact • Measurement	Levenson and Fink (2017)
HR analytics	*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****.*	• Decision-making practice • Technology • Statistical analysis	Marler and Boudreau (2017)
HR analytics	*is more than just metrics and/or scorecards, it consists of* ***various modeling tools*** *such as behavioural modeling, predictive modeling, impact analysis, cost-benefit analysis and ROI analysis to aid in* ***HR decision-making****.*	• Process to address impact • Metrics/modeling • Decision making	Sharma and Sharma (2017)
HR analytics	*is the* ***systematic identification*** *and* ***quantification*** *of the people-drivers of business outcomes, with the purpose of* ***making better decisions****.*	• Decision making	van den Heuvel and Bondarouk (2017)
HR analytics	*offers an opportunity to get better HR for less; link HR practices with business outcomes and value; challenge beliefs through data; educate practitioners on what works and what does not; improve* ***decision making*** *through* ***use of sound predictions****.*	• Decision making • Change management	van der Togt and Rasmussen (2017)
People analytics	*is the* ***use of data*** *about human behaviour, relationships and traits* ***to make business decisions*** *and helps to replace decision-making based on anecdotal experience, hierarchy and risk-avoidance with higher-quality decisions based on data analysis,* ***prediction*** *and experimental research.*	• Decision Making • Data/Data Analysis • Prediction	Nielsen and McCullough (2018)

Talent analytics	*Talent analytics is considered for recruitment and retention prediction as well as prescribing the solutions to issues such as employee attrition.*	• Decision making • Prediction	Sivathanu and Pillai (2020)
Workforce analytics	*refers to the **process** involved with understanding, qualifying, managing, and improving the role of talent in the execution of strategy and creation of value. It included not only a focus on metrics (e.g. what do we need to measure about our workforce?) but also analytics (e.g. how do we manage and improve the metrics we deem to be critical for business success).*	• Strategic decision-making process • Statistical metrics	Huselid (2018)
Workforce analytics	*is a **process** - one that is continuously advanced by improving problem solving through sound measurement, appropriate research models, systematic **data analysis**, and **technology** to support **organizational decision making**.*	• Decision-making process • Measurement/ data analysis • Technology	Mclver et al. (2018)

3.4.2 People Analytics Ownership Debate

Recently, scholars have begun to debate whether people analytics should remain within the domain of HR or be relocated into a centralized analytics team (Andersen, 2017; Fernandez & Gallardo-Gallardo, 2020; Marler & Boudreau, 2017; Minbaeva, 2018; Rasmussen & Ulrich, 2015; van den Heuvel & Bondarouk, 2017). A study conducted by van den Heuvel and Bondarouk (2017) found that 50% of respondents expect people analytics to become part of a centralized analytics team working independently of HR. Conversely, 35% of respondents suggested that people analytics would remain in HR, playing an essential role as a centre of excellence, offering data analysis in areas such as training, performance management, and compensation and benefits.

Those who argue for removing people analytics suggest that if kept solely within the HR function, it will miss out on opportunities to collaborate with other departments and stakeholders, gain access to data-rich sources, and limit its strategic potential. (Andersen, 2017; Fernandez & Gallardo-Gallardo, 2020; Rasmussen & Ulrich, 2015).

For example, Rasmussen and Ulrich (2015) have called for removing people analytics from HR, stating, "*Take HR analytics out of HR. This may sound drastic, but when HR analytics matures, it initially starts cooperating more with other departments' teams (in finance, operations, etc.), and eventually becomes part of cross-functional/end-to-end analytics — looking at human capital elements in the entire value-chain*" (p. 238).

Moreover, Marler and Boudreau (2017) argue that "*An appropriate collaboration between HR leaders and functional experts in disciplines such as finance, operations, marketing, and engineering may be key to developing the logical frameworks for HR analytics that can engage key decision-makers and connect more clearly to organizational outcomes*" (p. 19).

Similarly, Andersen (2017) states that those who suggest removing people analytics from HR argue that "*HR analytics will lose its strategic potential as HR in many organizations are more operational and tactical than strategically focused"* (p. 135). Moreover, he suggests that "*HR does not have ownership of all relevant data as many reside in finance (payroll), IT, legal, and sales*" (Andersen, 2017, p. 135), which is a critical issue when relying on various data sources to make evidence-based strategic workforce decisions.

In contrast, those who argue in favour of keeping people analytics within the HR department suggest that other functions such as finance, marketing or IT, will not be as committed to acting on the insights generated by workforce data and that people models will be built without HR interests in mind (Andersen, 2017; Angrave et al., 2016; Marler & Boudreau, 2017).

For example, Andersen (2017) suggests that *"nobody else cares about HR data and insights (as much as HR do), it takes HR knowledge to interpret and convert HR data to knowledge and information, it may make HR more data-driven and improve HR impact on business, data ownership sits naturally in HR and finally it will increase the likelihood of the analytics actually being used"* (p. 135).

Moreover, Angrave *et al.* (2016) state that "*If HR is not fully involved in the modelling process, there is significantly greater scope for models to be constructed in a way which fundamentally misunderstands the nature of human capital inputs*" (p. 7).

3.4.3 Ethical and Privacy Concerns of Using People Analytics

There has been a significant increase in organizations using information technology such as cell phones, email, social media, microphones, motion sensors, and wearable technology to collect and analyze real-time employee data (Hurrell, Scholarios, & Richards, 2017; Jeske & Calvard, 2020; Kane, 2015; Khan & Tang, 2017; Leonardi & Contractor, 2019; Strohmeier, 2018). Furthermore, AI, data mining, ML, and the internet of things (IoT) enable organizations to capture data related to employees' personal views, sentiments, and behaviours (Gelbard et al., 2018; Jeske & Calvard, 2020). For instance, in addition to collecting biographical data such as age, gender, and tenure, organizations have also begun to collect and analyze large amounts of relational data. This data includes movement patterns through Bluetooth technology, voice recordings that monitor whom employees interact with and with whom they are speaking to most frequently, and employee moods through facial recognition software (Gelbard et al., 2018; Kane, 2015; Leonardi & Contractor, 2019).

These new forms of collecting employee data present HR professionals and organizations with an emerging challenge concerning how to ensure the privacy and security of employee data while also navigating how data is being used and analyzed ethically (Falletta & Combs, 2020; Jeske & Calvard, 2020; Leonardi & Contractor, 2019).

According to Leonardi and Contractor (2019), "*Company-collected relational data, however, creates new challenges. Although most employment contracts give firms the right to record and monitor activities conducted on company systems, some employees feel that the passive collection of relational data is an invasion of privacy"* (p. 16).

Moreover, Khan and Tang (2017) suggest that "*Some seemingly well-intentioned and potentially useful endeavours to monitor key performance indicators, analyze areas 'in need of improvement', and optimize workforce scheduling and allocation can quickly spiral out of control, at least as viewed by the workforce, and could evoke visceral and negative responses from employees*" (p. 58).

Together with organizations enhancing their methods to monitor and collect data within the organization, this has led to the collection of employee data beyond the working environment, thus encompassing employee's personal and private lives blurring the lines and raising numerous ethical and privacy issues (Jeske & Calvard, 2020; Khan & Tang, 2017).

For instance, Jeske and Calvard (2020) suggest that organizations *"are able to monitor employees during their offsite activities via their mobile devices, network traffic and wearable devices"* (p. 249).

This is echoed by Khan and Tang (2017), who state that *"The boundaries of employee monitoring and related analytics are being extended from employees' work lives to well into their social and even physiological spaces"* (p. 63).

3.4.4 Missing Evidence of People Analytics Impact

Despite the increase in scholarly work and the popularity of people analytics among organizations, scholars have become more skeptical, questioning the legitimacy of people analytics and whether organizations should adopt people analytics altogether (Andersen, 2017; Angrave et al., 2016; Baesens et al., 2017; Levenson & Fink, 2017; Marler & Boudreau, 2017; McIver et al., 2018; Rasmussen & Ulrich, 2015).

First, evidence suggesting the success of people analytics remains rare, with organizations offering little evidence in support of the claims that people analytics can aid in strategic decision making (Baesens et al., 2017; Greasley & Thomas, 2020; Huselid, 2018; Levenson & Fink, 2017; Marler & Boudreau, 2017; Rasmussen & Ulrich, 2015).

For example, Marler and Boudreau (2017) claim that *"despite evidence of a growing interest in this innovation, we found very little and limited scientific evidence to aid decision-making concerning whether to adopt HR analytics"* (p. 20).

Additionally, according to Baesens, De Winne and Sels (2017), *"Although we see many companies ramping up investments in HR analytics, we haven't seen many success stories in that area yet"* (p.20).

Likewise, Rasmussen and Ulrich (2015) state that *"So far the published evidence supporting the alleged value of HR analytics is actually quite slim — it is currently based more on belief than evidence, and most often published by consultants with a commercial interest in* *the HR analytics market, while organizations rarely share the same success stories of business impact"* (p.236).

Second, very few organizations to date have moved beyond basic reporting, i.e. demographic reporting or presenting turnover statistics (Angrave et al., 2016; Gelbard et al., 2018; Levenson & Fink, 2017; Minbaeva, 2018), which has raised concerns regarding how people analytics can create value for organizations.

For instance, according to Angrave *et al.* (2016), "*despite the promise, successful strategic HR analytics projects appear to be few and far between. Although many organizations have begun to engage with HR data and analytics, most have not progressed beyond operational reporting".* (p. 4).

Furthermore, Levenson and Fink (2017) state that *"Many organizations still struggle to consistently produce sound descriptive data, and very few (as of 2016 only 8 percent of companies in Deloitte's global survey) report that they are fully capable of developing predictive models, let alone fully prescriptive models that directly outline specific action"* (p. 145).

Third, very few organizations have been able to evaluate and determine the business value that people analytics provides to their organizations (Andersen, 2017; Angrave et al., 2016; Baesens et al., 2017; Huselid, 2018; King, 2016; Marler & Boudreau, 2017; McIver et al., 2018; Rasmussen & Ulrich, 2015; Schiemann et al., 2018).

For example, Andersen (2017) claims that *"A few very large multinational companies have set up large HR analytics division and have embarked well on the journey. Many of their cases and results point to interesting and not least value-added findings"* (p. 134).

Moreover, McIver, Lengnick-Hall and Lengnick-Hall (2018) state that *"despite substantial publicity, a challenge remains for understanding how organizations can successfully use workforce analytics to influence organizational outcomes"* (p. 2).

This is echoed by Huselid (2018), who claims that *"Despite the recent popularity of workforce analytics, there is much that we do not yet know about the processes through which analytics affects the strategy execution process in organizations and, ultimately, firm success"* (p. 680).

3.4.5 Readiness to Perform People Analytics

3.4.5.1 Existing Skills Gap within HR Professionals

For people analytics to be successful and effectively enable organizations to make more informed and strategic data-driven decisions, HR professionals must possess a variety and diverse set of skills (Angrave et al., 2016; Harris et al., 2011; Kryscynski et al., 2018; Marler & Boudreau, 2017; McCartney et al., 2020; Rasmussen & Ulrich, 2015).

For example, Marler and Boudreau (2017) state that *"in order to implement HR analytics effectively, companies need employees with the right knowledge and skills to collect the correct data, perform the right statistical analyses and then to communicate the results in a meaningful and accessible way"* (p. 22).

Furthermore, Harris et al. (2011) argue that *"success with human capital analytics will depend, in large part, on HR's ability to find and nurture analytical talent – the people who produce the data, the quantitative analysis, and statistical models you need to make better decisions and achieve better results"* (p. 11).

Accordingly, academic literature has begun to propose and debate a wide range of skills and competencies required by HR professionals to effectively conduct people analytics (Andersen, 2017; Kryscynski et al., 2018; McIver et al., 2018; Minbaeva, 2018; van der Togt & Rasmussen, 2017; Vargas et al., 2018).

For example, according to Kryscynski et al. (2018), for HR to properly engage in analytics, *"HR professionals must have the abilities to perform the needed analyses. For the HR function to ensure appropriate measures, HR professionals must be able to individually* *identify appropriate data and information… HR professionals must have the ability to translate results into understandable and actionable insights for managers"* (p. 717).

Similarly, McIver et al. (2018) suggest four capability areas for people analytics, which are: *"(1) math and statistics, (2) programming and database skills, (3) domain knowledge in HR and behavioural science, (4) communication and visualization"* (p. 4).

Moreover, McIver et al. (2018) suggest that *"Workforce analytics professionals must be able to ask the right questions, determine the right metrics, and provide evidence that enables strategic decision makers to understand trade-offs among alternative courses of HR actions (policies, practices, investments)"* (p. 10).

Recently, taking these perspectives into account, McCartney et al. (2020) have developed a competency model for HR Analysts where they "*offer evidence supporting a set of six distinct competencies required by HR Analysts including consulting, technical knowledge, data fluency and data analysis, HR and business acumen, research and discovery and storytelling and communication*" (p. 1)

Although fundamental, there exists a lack of analytical understanding in HR departments, which has been cited as a significant issue and barrier to the success of people analytics in organizations (Andersen, 2017; Angrave et al., 2016; Fernandez & Gallardo-Gallardo, 2020; Greasley & Thomas, 2020; Peeters et al., 2020). For instance, many of the competencies and skills required by HR professionals to conduct people analytics are not currently found within HR departments but rather reside elsewhere within the organization (Green, 2017; Ulrich & Dulebohn, 2015; van den Heuvel & Bondarouk, 2017). As a result, this dearth of competencies, skills, and overall analytical thinking has begun to raise concerns and generating considerable skepticism of HR's ability to effectively utilize people data to increase organizational performance (Andersen, 2017; Angrave et al., 2016; Boudreau & Cascio, 2017;

Green, 2017; King, 2016; Kryscynski et al., 2018; Marler & Boudreau, 2017; Minbaeva, 2018; van den Heuvel & Bondarouk, 2017).

According to Angrave et al. (2016), *"the development of HR analytics is being hampered by a lack of understanding of analytical thinking by the HR profession"* (p. 1).

Also, Marler and Boudreau (2017) claim that *"less than one third of HR analytics professionals reported having competency in advanced multivariate statistics and that proportion drops to only 3% when only considering HR professionals not specifically hired for HR analytics"* (p. 19).

3.4.5.2 Questionable Data Quality

High-quality data is essential for conducting value-added people analytics (Fernandez & Gallardo-Gallardo, 2020; Jeske & Calvard, 2020). However, many organizations still struggle to have confidence in their HR and people data (Andersen, 2017; Boudreau & Cascio, 2017; Jeske & Calvard, 2020; King, 2016; McIver et al., 2018; Minbaeva, 2018; Pape, 2016). For example, in a Deloitte study (2017) of over 10,000 business and HR leaders (as cited in McIver et al., 2018), only 8% of HR leaders surveyed reported being confident using the data they have access to. Therefore, attaining and maintaining high-quality data has become a significant limitation faced by HR departments. This difficulty arises as workforce data tend to be vast, messy, constantly changing, and held in several different data sources (Andersen, 2017; Boudreau & Cascio, 2017; Harris et al., 2011; Levenson & Fink, 2017; McIver et al., 2018; Minbaeva, 2018).

For example, according to Minbaeva (2018), *"most firms do not know what types of data are already available to them or in what form. In fact, most firms do not have the answers to some basic questions: What data do we have? Where do we store it? How was the data collected? … Such poor organization of firm data can be very costly"* (p. 702).

Moreover, the lack of organization and centralized storage location for data leads to several issues, including data duplication, incorrect and inaccurate entries, and missing data (Boudreau & Cascio, 2017; King, 2016; Levenson & Fink, 2017; Minbaeva, 2018). Furthermore, Andersen (2017) suggests that the lack of data quality in HR can be attributed to the lack of a coherent data strategy, not understanding the strategic importance of data, poor data management, and a lack of critical data sources.

3.5.4.3 Outdated or Unsophisticated HR Technology

Continuous investment in HR technology over the past 15 years has played a significant role in developing and executing people analytics (Boudreau, 2017; Marler and Boudreau, 2017). HRIS serves as a foundation for people analytics by enabling HR departments to collect, extract, and analyze large amounts of data (King, 2016; Marler & Boudreau, 2017; McIver et al., 2018; Sharma & Sharma, 2017). Moreover, HRIS offers HR professionals better insight into the workforce as they provide the capability to produce interactive dashboards and scorecards which highlight key workforce measures in several areas such as compensation, employee engagement, employee performance, diversity and inclusion, and talent management (Aral et al., 2012; Kapoor & Sherif, 2012; Marler & Boudreau, 2017; van der Togt & Rasmussen, 2017). However, scholars have begun to call into question the functionality of HR technology, suggesting that although they can collect and extract data, they fail to deliver the appropriate solutions necessary for performing advanced and predictive analytics (Andersen, 2017; Angrave et al., 2016; Boudreau & Cascio, 2017; Fernandez & Gallardo-Gallardo, 2020; King, 2016; Marler & Boudreau, 2017).

For example, Angrave et al. (2016) suggest that *"Rather than providing strategic and predictive analytics that allow organizations to ask and answer big questions about how value can be created, captured and leveraged, HRIS typically provide answers to a more limited set* *of questions focused on operational reporting … the costly analytics capabilities provided by the latest forms of HRIS are failing to deliver strategic HR analytics capabilities"* (p. 5).

Similarly, King (2016) suggests that *"the ability for analytics to be applied in a meaningful way has been hindered, not helped, by the growing HR analytics industry, which is often built upon products and services that fail to meet the needs of HR professionals and organizations"* (p. 491).

Likewise, Fernandez & Gallardo-Gallardo (2020) state that *"developers of software for predictive and prescriptive HR analytics do not understand the contextspecific causality of each organization and that managers do not have the knowledge and skills to adapt their environment to the standard model proposed in the software"* (p. 14). Thus, becoming more of an impediment and barrier to people analytics.

To address this lack of functionality, organizations have begun to adopt and use additional forms of information technology such as business intelligence (BI) and data analytics platforms to generate HR intelligence through their workforce data (Kapoor & Sherif, 2012; Sivathanu & Pillai, 2020). BI and data analytics platforms enable HR professionals to form predictions and to make more informed data-driven decisions through the use of online analytical processing (OLAP), data mining techniques, perform advanced statistical analysis, and the development of analytical models for forecasting and engaging in predictive analytics (Kapoor & Sherif, 2012).

3.5 Discussion and Future Research

People analytics has evolved in several areas and directions over the past decade. To better comprehend the potential future of people analytics, this study synthesized and critically evaluated the significant increase of peer-reviewed articles focused on people analytics published in ABS ranked journals between 2011 and 2020. This study conducted a thematic analysis, adopting a strict and comprehensive coding process to ensure the validity of the emerging themes, debates, and issues within the existing people analytics literature. Additionally, this allowed for the critical evaluation of the potential future direction and maturity of people analytics.

3.5.1 The Promise of People Analytics

The promise that people analytics will allow organizations to make more evidence-based decisions and, in return, positively impact organizational performance underscores the current state of this developing area of research. People analytics has been considered a "game-changer" for the future of HR (van der Togt & Rasmussen, 2017), with the potential to further transform HR into a strategic business partner. Furthermore, advocates and supporters of people analytics also claim that by utilizing people analytics, organizations are more able to efficiently identify underlying patterns and trends in their workforce data, offering organizations a competitive advantage (Leonardi & Contractor, 2019; McIver et al., 2018; Schiemann et al., 2018; van der Togt & Rasmussen, 2017). As such, organizations have made significant investments in people analytics by purchasing and implementing HR technologies.

In practice, organizations have begun to form people analytics teams to gain competitive advantage (Peeters et al., 2020). These teams are tasked with exploiting insights derived from employee data in areas such as recruitment and selection, employee engagement, diversity and inclusion, and retention and turnover (Falletta and Combs, 2020; Peeters, Paauwe and Van De Voorde, 2020). Several published case studies and organizational success stories demonstrate this, detailing how organizations have leveraged people analytics to enable their HR departments to address HR challenges. These success stories offer organizations hope that if their HR departments can effectively use workforce data coupled with sophisticated predictive analytics, they too can transform their HR department into a more strategic data-driven organizational function and positively impact organizational performance.

3.5.2 The Reality of People Analytics

In contrast, despite the promises offered by people analytics, the current reality of people analytics programs is more skeptical than optimistic, with several issues and debates generating more questions than answers. Although people analytics are being widely implemented to aid in making workforce decisions, it remains unclear what people analytics is. For instance, some scholars consider it an organizational practice (Marler & Boudreau, 2017; Minbaeva, 2018), whereas others consider it an HR process (Huselid, 2018; McIver et al., 2018). Similarly, an agreement has yet to be reached on the concept of people analytics as various terms such as HR analytics, workforce analytics, human capital analytics, and HR metrics have been used synonymously to describe the concept (Huselid, 2018). Confusion between the terms and their associated definitions highlights a significant need for further clarity on what constitutes people analytics. Furthermore, this inconsistency raises concerns given that current definitions do not adequately address the depth of people analytics or actively elaborate on the various stages of people analytics maturity. Accordingly, the reality of people analytics is not a "one-size-fits-all" solution, as suggested in the extant literature. Instead, people analytics is situational and falls along a spectrum, where organizations at the low end of maturity report on descriptive statistics, whereas organizations at the highest and most mature level of people analytics utilize AI and ML to analyze historical and real-time workforce data to perform predictive and prescriptive analytics.

Equally important are the issues raised concerning whether the HR function is poised and ready to engage in people analytics. The current reality and a common theme faced by most organizations in their people analytics journey is a shortage of analytical understanding and high-quality, trustworthy data needed to conduct people analytics. Moreover, existing HR technology may not be sophisticated enough or too outdated to perform predictive and prescriptive people analytics. Considering that analytical understanding, technology, and high-quality, trustworthy data are critical for people analytics success, missing any one of these elements significantly hinders the ability of people analytics to generate actionable insights. For example, if people analytics teams do not have the analytical understanding and capabilities to run analysis, having high quality and reliable data offers HR departments no value since, without these competencies and skills, team members will not gain valuable insight from the data. Likewise, if teams cannot trust HR data given the likelihood of missing values and wrong entries, having the analytical understanding and capabilities will only aid in running inaccurate analysis, thus generating little to no value. These gaps call into question HR's readiness to adopt people analytics altogether, perpetuating the emerging argument and debate on whether people analytics may benefit from being removed from the HR function and ownership be transferred to a centralized analytics department.

Lastly, the influence of people analytics and organizations using technology, including AI, to collect, analyze, and make decisions with sensitive workforce data, is a serious issue involving employee privacy, security, and overall ethical organizational practices. For example, preserving employee privacy presents a significant HR challenge as organizations continue to collect workforce data from various mediums such as text messages, email, social media, microphones, motion sensors, and wearable technology. These forms of employee monitoring infringe upon workers' privacy by continuously monitoring them inside and outside their place of employment. Furthermore, more advanced forms of technology such as wearables (i.e. smartwatches, chip implants, body-tracker devices, etc.) carry their own set of privacy issues as they can report on sensitive health metrics (i.e. weight, diet, exercise, stress levels, and sleep patterns). This data can then be exploited by organizations to make workforce decisions which have raised several concerns from the perspective of employees (Khakurel, Melkas, & Porras, 2018).

3.5.3 The Future of People Analytics

Despite its continued growth and increasing interest over the past several years, people analytics remains an underdeveloped and underexplored discipline within HRM research. Consequently, this presents academics and practitioners with a unique opportunity to make significant contributions and shape the direction and the future of people analytics research. Together with the growing interest and usage of people analytics in practice, academic research plays a fundamental role in furthering the field of people analytics. Such research offers insight into how HR can effectively respond to the challenges and opportunities presented by the digitalization of HRM. Accordingly, this study provides seven research questions aimed at inspiring further research that will help narrow the gap between the promise and reality of people analytics as well as stimulate discussion and perhaps new debates within the field.

3.5.3.1 How Can Researchers Bridge the Academic-Practitioner Gap?

A shared understanding of people analytics among researchers and practitioners is required as the field continues to evolve rapidly. This shared understanding is critical, as a collaboration between practitioners and researchers can significantly help address many of the debates and challenges people analytics currently faces. For example, due to the inconsistencies among the varying definitions, it remains difficult for researchers to appropriately conduct research demonstrating the impact of people analytics on organizational and employee outcomes.

In contrast, the research-practice gap creates challenges for practitioners as well. Building on the example above, without a clear understanding of people analytics, organizations and practitioners will be less able to adopt and implement people analytics consistently and effectively. Consequently, this could lead to the failure of people analytics adoption and implementation, with very few organizations being able to successfully evaluate and benchmark their people analytics efforts with other organizations. Therefore, future research in people analytics is encouraged to adopt a strong collaborative and practice-focused approach through mediums such as action research (Lewin, 1946) and engaged scholarship (Van de Ven, 2007). Employing these research methodologies will facilitate discourse among people analytics stakeholders offering the opportunity to develop relevant knowledge through the generation of specific research questions, building theories, and translating insights into practical solutions (Bleijenbergh, van Mierlo, & Bondarouk, 2020; Short, 2006; Van de Ven, 2007).

3.5.3.2 What Skills are Most Influential to People Analytics Success and How can People Analytics Aid in Acquiring and Developing People Analytics Skills?

The digital transformation and shift of HRM influenced by the adoption and implementation of information technology will significantly impact the demands and responsibilities of HR professionals moving forward (Cohen, 2015; Stone, Deadrick, Lukaszewski, & Johnson, 2015b). Although much research has been conducted identifying the skills and competencies required by HR professionals to perform people analytics, what remains unclear is which skills are most influential to people analytics success. Likewise, research investigating how HR departments can effectively use people analytics to acquire and develop highly specialized skill sets is unexplored in the existing literature. Together, these gaps present a significant opportunity for researchers to further investigate what skills are needed for people analytics success and how people analytics can be used to acquire specific competencies and skills that can lead to competitive advantage. Therefore, further research should conduct longitudinal studies focused on empirically testing various individual skills and their impact on people analytics success.

Additionally, research should also focus on how people analytics can help facilitate the acquiring and development of people analytics professionals. For example, how can people analytics influence succession planning activities, and how can people analytics be leveraged to identify members of the organization who may be suitable for filling hard-to-fill roles and internal vacancies? In other words, how can people analytics be used to create and develop human capital resources within an organization?

3.5.3.3 What Existing Theories Can Offer Insight into Evaluating People Analytics Success?

People analytics research has primarily focused on the application of people analytics rather than examining the phenomenon from a theoretical perspective (Minbaeva, 2017, 2018). As a result, there is a significant need for more empirical work demonstrating the theoretical relationship between people analytics and overall organizational performance (McIver et al., 2018; Minbaeva, 2017, 2018).

Additionally, there is little evidence to support that organizations employing advanced forms of technology such as AI and ML to aid in HR decision-making see any additional value regarding organizational performance (Gelbard et al., 2018). Likewise, it is essential for people analytics scholars to examine how people analytics can provide value at the organizational, team and individual levels, and how this success is measured and evaluated. This research area is critically important in the development of people analytics as there is currently little evidence linking people analytics to HR outcomes, making it unclear whether organizations should be investing in people analytics altogether. Against this backdrop, researchers should focus on theorizing and linking people analytics to various multi-level outcomes through existing human capital and HRM theories to strengthen the argument for adopting people analytics. Table 3.5 offers several examples of research areas and potential theoretical lenses that could be adopted to examine the impact and success of people analytics.

Table 3.5 Examples of Future Research Avenues for People Analytics Researchers

Level of Analysis	Areas for Further Research	Theoretical Lenses
Individual	How can people analytics aid in addressing issues concerning: Employee engagement Employee trust Employee well-being Green HRM Practices HR development Job satisfaction Recruitment and selection Turnover/turnover intention	Agency Theory AMO (Ability-Motivation-Opportunity) Equity Theory Human Capital Information Boundary Theory Job Demands Resource Model Social Exchange Theory
Team	What makes people analytics teams successful? What is the ideal team size and most important roles found within people analytics teams? Does team size and role differ between level of analytics maturity and industry sector? How can people analytics teams contribute to HR outcomes? How is people analytics success defined and measured?	Human Capital Human Capital Resources Framework Theory of Human Capital Complementarities Complex Adaptive Systems Theory Actor Network Theory
Organizational	Do organizations that use advanced technology and people analytics benefit more than those organizations who do not? Linking people analytics to organizational outcomes including: Innovation Sustainability Navigating times of change and crisis	Resource-Based View Knowledge-Based View Dynamic Capabilities Resource Orchestration

3.5.3.4 What Ethical and Privacy Concerns Arise as a Result of People Analytics?

As organizations continue to utilize technology to collect and analyze higher volumes of sensitive employee data to make workforce decisions, this raises several concerns around employee privacy and data security, a concept that is currently underdeveloped within the existing people analytics literature. For example, collecting and exploiting sensitive workforce data (i.e. social network data, sensitive health metrics) raises several ethical concerns, including what types of employee data are too invasive to collect? How and when should organizations monitor employees with these new forms of technology? And how does the implementation of AI and ML techniques and methodologies integrate with existing HRM decision-making without being too invasive? It also questions whether sensitive employee data should be exploited for the benefit of increasing organizational performance.

Similarly, the "dark side" and potential negative impact of using AI and people analytics on employee job outcomes such as job satisfaction, organizational justice, employee well-being, and trust have not been significantly addressed within the extant people analytics literature. For example, from the perspective of organizational injustice, if HR departments begin to make decisions through the output of an algorithm rather than human experience and intuition, this proposes the question of at what point could people analytics do more harm than good? Furthermore, as HR departments continue to adopt AI and ML technology to perform and automate various HR deliverables, it will become critically important to understand the impact and the fallout that this may have on employees and HR data governance policies. For example, will employees trust AI algorithms to make organizational decisions that affect their livelihood? Thus, future research is recommended to explore the ethical, privacy, and security implications of using sensitive workforce data. Such research should simultaneously address employee perceptions and the potential negative impact of people analytics on employee job outcomes such as job satisfaction, employee engagement, organizational trust, etc.

Additionally, research examining how data governance policies need to evolve to account for AI and ML adoption is also of utmost importance.

3.5.3.5 Does Ownership of People Analytics Matter?

Recently, some scholars have begun to question whether HR should retain ownership of people analytics or whether it is more appropriate for the function to be relocated outside of HR. Each side of this debate has merit. For instance, keeping people analytics within the HR function allows insights gathered from people analytics to be interpreted within the context of HR. Thus, offering and developing solutions that can aid in addressing specific HR challenges. Likewise, keeping people analytics within HR will alleviate any issues regarding data privacy as moving people analytics outside HR will pose a risk around what sensitive data is available and being used by those in non-HR roles.

Furthermore, removing people analytics from the HR function may suggest to the HR department that they are not seen as strategic partners. The alternative perspective of moving people analytics outside of HR focuses on the lack of analytical skills, data quality, and outdated technology currently found within the HR department. For example, there appears to be a significant shortage among HR professionals who possess the required skills and competencies to perform people analytics. Additionally, those who suggest the removal from HR claim that keeping people analytics within HR hinders their ability to collaborate and access data from other departments such as finance, IT, or marketing. Despite the claims made by each side of this debate, at this point, it is just speculation as to where people analytics should reside. To offer insight into this debate, perhaps instead of asking who should take ownership of people analytics, the question posed should be what impact does people analytics have on the organization depending on their organizational reporting structure. In other words, does having people analytics in HR or outside of HR have a more significant business impact?

Future research is encouraged to conduct longitudinal studies to add clarity by examining the success of people analytics teams both inside and outside the HR function.

3.5.3.6 Can People Analytics Empower Employees and Organizations in Times of Crisis?

The Covid-19 pandemic has caused major disruption over the past year, forcing organizations globally to adapt to the unprecedented shift in workplace demands. In light of Covid-19, organizations have taken several precautions to preserve their employees physical and psychological health and well-being. For example, more employees are working from home to reduce their risk of exposure and spreading the virus. However, as a result of these safety measures, employees could develop adverse outcomes regarding mental well-being, engagement, and productivity. For instance, employees may feel less connected to their coworkers and team members due to the inability to interact with them face-to-face. The pandemic and the "new normal" moving beyond Covid-19 has given rise to the opportunity for people analytics to play a vital role in aiding leadership in times of crisis and transition, to make informed and strategic workforce decisions quickly. Accordingly, future research should examine how people analytics can help leadership navigate and influence decision-making in times of crisis. More broadly, research should explore how people analytics can empower employees and organizations in times of turbulence and change.

3.5.3.7 Can People Analytics Impact the Growing Need for Sustainability and Facilitate the Adoption of "Green HRM" Practices?

One of the most pressing issues facing our planet in the 21st century is climate change and environmental sustainability (Guerci, Longoni, & Luzzini, 2016; Jerónimo, Henriques, Lacerda, da Silva, & Vieira, 2020; Kumar & El-kassar, 2019; Pham, Hoang, & Phan, 2019). As a result, more organizations have become environmentally aware, looking for ways to improve their ecological footprint via green supply chain management and green IT systems

(Dubey et al., 2019; Kumar & El-kassar, 2019; Yang, Li, & Kang, 2020). Likewise, several organizations have begun to apply big data analytics as a method to further develop sustainable capabilities and improve their organization's overall environmental sustainability (Dubey et al., 2019; Kumar & El-kassar, 2019). Within the context of HRM, HR departments have begun to implement various green initiatives known as “Green HR” to develop environmentally friendly and sustainable HR practices (Jerónimo et al., 2020; Pham et al., 2019). These practices include green hiring, green training, green compensation, and green health and safety (Jerónimo et al., 2020; Pham et al., 2019). Much like big data analytics at the organizational level, future research should be undertaken to better understand how people analytics can act as an enabler and a facilitator for the support and development of green hr practices within organizations.

3.6 Conclusion

Although considerable progress has been made in the emerging area of people analytics, it is evident that the field has much to overcome concerning the challenges raised within this review. As such, this systematic review set out to offer a greater level of understanding of people analytics by synthesizing and critically evaluating the people analytics literature produced between 2011 and 2020. Drawing on 42 peer-reviewed articles representing 26 ABS ranked journals, this review offers insight into what debates and issues are emerging as a result of people analytics adoption. As a result, this review presents a comprehensive research agenda demonstrating the need for collaboration between scholars and practitioners to successfully align the promise and the current reality of people analytics.

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3.8 Appendix A. Summary of ABS Ranked Journal Articles (42) Included in the Present Review

Author	Article Title	Journal	Method/Type of Paper	Summary
Harris et al. (2011)	Talent and Analytics: New Approaches, Higher ROI.	*Journal of Business Strategy*	Case Study	Presents six analytical tools for HR and several case studies demonstrating how organizations globally are using people analytics to solve business challenges.
Aral et al., (2012)	Three-way complementarities: Performance Pay, human resource analytics, and information technology	*Management Science*	Quantitative Survey of 189 organizations	An empirical study which discusses how information technology can complement both performance pay and people analytics.
Kapoor and Sherif (2012)	Human resources in an enriched environment of business intelligence	*Kybernetes*	Viewpoint based on Experience	Discusses how the utilization of business intelligence (BI) tools in HR can aid in solving HR challenges in the constantly evolving business environment.
Kane (2015)	People Analytics' Through SuperCharged ID Badges	*MIT Sloan Management Review*	Case Study	Discusses emerging technology currently being implemented in organizations to collect workforce data. Presents a case study demonstrating how the new technology works.
Rasmussen and Ulrich (2015)	Learning from practice: how HR analytics avoids being a management fad	*Organizational Dynamics*	Case Study	Presents two case studies on how organizations are using people analytics to solve business challenges.

Ulrich and Dulebohn (2015)	Are we there yet? What's next for HR?	*Human Resource Management Review*	Conceptual	Highlights the evolution and transformation of HR as a function and presents conceptual models for the future of HR.
Angrave et al., (2016)	HR and analytics: Why HR is set to fail the big data challenge	*Human Resource Management Journal*	Qualitative Interviews and Literature Reviews	Critiques the discipline of people analytics and highlights several challenges and barriers facing people analytics.
King (2016)	Data Analytics in Human Resources: A Case Study and Critical Review	*Human Resource Development Review*	Case Study	Provides an overview of people analytics including definitions, the application of, and drawbacks of people analytics. Offers a case study of people analytics being used to solve business challenges.
Pape (2016)	Prioritising data items for business analytics: Framework and application to human resources	*European Journal of Operational Research*	Case Study	Discusses how business intelligence can be used in HR by presenting a case study on how organizations can leverage people analytics to solve business challenges.
Andersen (2017)	Human capital analytics: the winding road	*Journal of Organizational Effectiveness: People and Performance*	Viewpoint based on Experience	Offers insight into several areas where people analytics is experiencing challenges in adoption including maturity, mindset, organization, and competencies.
Baesens et al., (2017)	Is Your Company Ready for HR Analytics?	*MIT Sloan Management Review*	Viewpoint based on Experience	Offers four lessons on how to successfully leverage people analytics to support making strategic workforce decisions.
Boudreau and Cascio (2017)	Human capital analytics: why are we not there?	*Journal of Organizational Effectiveness: People and Performance*	Conceptual	Discusses the "LAMP" and outlines four elements of why people analytics are not being "pushed" toward their audience including logic, analytics, measures, and process. Additionally, five conditions are discussed as to why the

				wider use of people analytics is not "pulled" in by the analytics user.
Green (2017)	The best practices to excel at people analytics	*Journal of Organizational Effectiveness: People and Performance*	Viewpoint based on Experience	Provides 16 best practices for conducting people analytics.
Khan and Tang (2017)	The paradox of human resource analytics: being mindful of employees	*Journal of General Management*	Quantitative	Through the use of a survey, the authors discuss and provide empirical evidence around the relationship between people analytics and employees affective commitment.
Levenson and Fink (2017)	Human capital analytics: too much data and analysis, not enough models and business insights	*Journal of Organizational Effectiveness: People and Performance*	Literature Review	Addresses the barriers associated with the exponential growth and implementation of people analytics within organizations.
Marler and Boudreau (2017)	An evidence-based review of HR Analytics	*International Journal of Human Resource Management*	Evidence Based Literature Review	Provides the first evidence-based review of the field of people analytics analyzing 14 people analytics articles. Offers significant insight into the developing field of people analytics.
Minbaeva (2017)	Human capital analytics: why aren't we there? Introduction to the special issue	*Journal of Organizational Effectiveness: People and Performance*	Guest Editorial	Guest editorial and introduction to the special issue. Offers an overview of the special issue.
Sharma and Sharma (2017)	HR analytics and performance appraisal system: A conceptual framework for	*Management Research Review*	Conceptual	Suggests the use of people analytics will be negatively related to subjectivity bias in performance appraisal positively affecting employees' perceived accuracy and fairness.

	employee performance improvement			
van den Huevel and Bondarouk (2017)	The rise (and fall?) of HR analytics	*Journal of Organizational Effectiveness: People and Performance*	Qualitative Interviews	Interviewing 20 participants working in 11 Dutch organizations, the authors discuss the evolution of people analytics and what the future of people analytics might look like in 2025.
Van der Togt and Rasmussen (2017)	Toward evidence-based HR	*Journal of Organizational Effectiveness: People and Performance*	Viewpoint based on Experience	Offers a practitioner's viewpoint on the challenges currently faced by people analytics, future direction of the field, and the value currently created by people analytics.
Buttner et al., (2018)	A representative organizational diversity metric: a dashboard measure for executive action	*Equality, Diversity and Inclusion: An International Journal*	Case Study	Provides a specific case study which demonstrates how people analytics can positively impact diversity and inclusion within organizations.
Huselid (2018)	The science and practice of workforce analytics: introduction to the HRM special issue	*Human Resource Management*	Guest Editorial	Guest editorial and introduction to the special issue. Offers an overview of the special issue. Offers a definition in addition to several areas of future research for the field of people analytics.
Gelbard, Gonen, Carmeli, & Talyansky (2018)	Sentiment Analysis in Organizational Work: Towards an Ontology of People Analytics	*Expert Systems*	Conceptual and Sentiment Analysis	Using six human resource constructs, the paper uses sentiment analysis to propose a conceptual ontology for the field of people analytics drawing on a case study of Enron.
Kryscynski et al., (2018)	Analytical abilities and the performance of HR professionals	*Human Resource Management*	Quantitative using 360 degree feedback surveys from 1,117 HR professionals	Discusses the importance of analytical skills in HR and provides empirical evidence that HR professionals who are more analytical are overall better performers.

Levenson (2018)	Using workforce analytics to improve strategy execution	*Human Resource Management*	Conceptual	Discusses a three step approach to conducting workforce analytics aimed at improving strategy, execution and organizational effectiveness through the application of systems diagnostics.
McIver et al., (2018)	A strategic approach to workforce analytics: Integrating science and agility	*Business Horizons*	Conceptual	Proposes several ways to overcome the misunderstanding of how to use people analytics for organizational success through the integration of agile development.
Minbaeva (2018)	Building creditable human capital analytics for organizational competitive advantage	*Human Resource Management*	Conceptual	Argues that people analytics should be an organizational capability which is made up of three dimensions-- data quality, analytical competencies, and the strategic ability to act.
Safarishahrbijari (2018)	Workforce forecasting models: A systematic review	*Journal of Forecasting*	Systematic Literature Review	Systematic literature review exploring the extant literature of workforce forecasting.
Schiemann et al., (2018)	Putting human capital analytics to work: Predicting and driving business success	*Human Resource Management*	Case Study	Presents a case study on how organizations are using people analytics to solve business challenges.
Simón and Ferreiro (2018)	Workforce analytics: A case study of scholar-practitioner collaboration	*Human Resource Management*	Case Study	Presents a case study of a Spanish retail firm who has implemented people analytics to solve business challenges.
Tursunbayeva et al., (2018)	People analytics—A scoping review of conceptual boundaries and value propositions	*International Journal of Information Management*	Scoping Literature Review	A mixed method scoping review of the extant people analytics literature. Specifically focuses on the technology and tools element of people analytics.

Vargas et al., (2018)	Individual adoption of HR analytics: a fine grained view of the early stages leading to adoption	*International Journal of Human Resource Management*	Quantitative survey comprised of 123 HR specialists/generalists	Applies innovation theory and the theory of planned behaviour to examine the individual adoption of people analytics among employees.
Ben-Gal, (2019)	An RIO-based review of HR Analytics: practical implementation tools	*Personnel Review*	Systematic Literature Review	Systematic literature review offering an ROI based review of people analytics and its application within organizations.
Leonardi and Contractor (2019)	Better People Analytics - Measure who they know not just who they are	*Harvard Business Review*	Conceptual	The article presents a framework for understanding and applying relational analytics as it relates to the HR function.
Falletta & Combs (2020)	The HR Analytics Cycle: a seven-step process for building evidence-based and ethical HR analytics capabilities	*Journal of Work-Applied Management*	Conceptual	The paper discusses the meaning of people analytics and develops a seven-step people analytics cycle aimed at aiding organizations in achieving their strategic objectives.
Fernandez & Gallardo-Gallardo (2020)	Tackling the HR digitalization challenge: key factors and barriers to HR analytics adoption	*Competitiveness Review*	Systematic Review	A systematic review examining what does people analytics encompass and identifying barriers which impede the adoption of people analytics in organizations.
Greasley & Thomas (2020)	HR analytics: The onto-epistemology and politics of metricised HRM	*Human Resource Management Journal*	Qualitative	The paper explores the increasing influence of positivistic and EBM approached to people analytics projects, how they are mobilized, and how analytics projects can influence practice.
Jeske & Calvard (2020)	Big data: lessons for employers and employees	*Employee Relations*	Viewpoint	The focus of the article is to further examine and critically reflect on the debate of using employee data in big data projects.

McCartney et al., (2020)	21st Century HR: A Competency Model for the Emerging Role of HR Analysts	*Personnel Review*	Qualitative	The study develops a competency model for the role of “HR Analyst” identifying 6 competencies including consulting, technical knowledge, data fluency and data analysis, HR and business acumen, research and discovery and storytelling and communication
Peeters et al., (2020)	People analytics effectiveness: developing a framework	*Journal of Organizational Effectiveness: People and Performance*	Viewpoint	The paper focuses on people analytics teams and how they can add to organizational performance. The authors also present the “People Analytics Effectiveness Wheel”
Pessach et al., (2020)	Employees recruitment: A prescriptive analytics approach via machine learning and mathematical programming	*Decision Support Systems*	Empirical	The paper proposes an analytical framework using machine learning that HR professionals can use to improve hiring decisions.
Sivathanu & Pillai (2020)	Technology and talent analytics for talent management – a game changer for organizational performance	*International Journal of Organizational Analysis*	Viewpoint	The aim of the paper is to examine how technology can be used for the purpose of talent management and its overall impact on organizational performance.

CHAPTER 4 STUDY 2 – COMPLEMENTARITY HUMAN CAPITAL: LINKING ANALYTICAL AND STORYTELLING SKILLS TO PEOPLE ANALYTICS PERFORMANCE

4.1 Abstract

Purpose – Despite the growing number of case studies and qualitative research projects that identify analytical and storytelling skills as the two broad human capital inputs required to perform people analytics, the direct impact of analytical and storytelling skills on enhancing people analytics performance remains unknown. Drawing on the strategic human capital literature, this study aims to uncover how analytical and storytelling skills, two valuable types of human capital, independently and collectively lead to higher levels of people analytics performance.

Design/methodology/approach – Using a sample of 173 people analytics professionals, hierarchical linear modelling was performed to test the direct and complementarity effects of analytical and storytelling skills on people analytics task and team performance.

Findings – The results suggest that storytelling skills are positively associated with people analytics task and team performance. In addition, a complementarity effect was found whereby storytelling skills strengthen the positive impact of analytical skills on HR Analyst task performance and team performance.

Practical implications – The results highlight the importance of storytelling for people analytics professionals. More specifically, the findings suggest that people analytics professionals should concentrate on building their people analytical capability as well as their storytelling skills so that they can effectively analyze, interpret, and translate insights into a compelling data story.

Originality/value – The paper makes two significant contributions to people analytics and strategic human capital. First, the study responds to several calls for research investigating the

KSAOs that are most influential to people analytics performance. Second, the study extends the current understanding of human capital's direct and complementarity impact on performance.

Keywords: *Human Capital, Human Capital Complementarities, People Analytics, People Analytics Performance, Strategic HRM*

4.2 Introduction

The HR landscape is currently undergoing a significant shift, as evidenced by technological disruptions and the prominence of using big data, AI, and ML to make more evidence-based decisions (Fernandez & Gallardo-Gallardo, 2020; Harney & Collings, 2021; Minbaeva, 2021; Strohmeier, 2018). This *digital revolution* has led to the rapid growth and adoption of people analytics, with many academic researchers investigating why and how people analytics can add value to organizations through enhanced decision-making practices (Harris et al., 2011; Minbaeva, 2018, 2021; Rasmussen & Ulrich, 2015; Sivathanu & Pillai, 2020). Recently, scholars have taken a human capital perspective (Becker, 1964) and claim that it is the KSAOs of the individuals performing people analytics tasks that create value (Andersen, 2017; Kryscynski et al., 2018; McCartney et al., 2020; McIver et al., 2018; van der Togt & Rasmussen, 2017). For example, according to Kryscynski et al. (2018), HR professionals with higher analytical ability are perceived to have better job performance. Likewise, McCartney et al. (2020) suggest that HR Analysts represent a human capital resource given their specialized set of KSAOs that allows them to create knowledge and insights from data enabling organizations to make evidence-based decisions leading to higher performance.

Innately, people analytics requires a diverse range of KSAOs to acquire and transform workforce data into actionable insights. For example, on the one hand, scholars have suggested analytical skills such as statistics and testing statistical models, working with diverse technical programs including PowerBI, Tableau, R, and Python, and having a high aptitude for data literacy are required for successful people analytics (Andersen, 2017; Falletta & Combs, 2020; McCartney et al., 2020; Minbaeva, 2018; Mishra, Lama, & Pal, 2016). On the other hand, research also claims that storytelling skills are a critical component of people analytics, given its ability to frame complex data into actionable insights and gain managerial buy-in (Andersen, 2017; McCartney et al., 2020; Minbaeva, 2018; van der Togt & Rasmussen, 2017). For example, according to Andersen (2017), only by framing analytics in a compelling story can data be used to improve decision-making and add value. Likewise, Davenport and Kim (2013) emphasize the importance of storytelling skills in identifying problems and presenting outcomes to encourage effective organizational decision-making. Taken together, analytical and storytelling skills enable people analytics to add value for organizations through the ability to analyze workforce data and translate insights into a common or shared language.

Despite the growing number of case studies and qualitative research projects that identify analytical and storytelling skills as the two broad human capital inputs required to perform people analytics, the direct impact of analytical and storytelling skills on enhancing people analytics performance remains unknown (Andersen, 2017; Huselid, 2018; McCartney et al., 2020; McIver et al., 2018; Minbaeva, 2018; Peeters et al., 2020). As such, this study draws on the strategic human capital literature to hypothesize that analytical and storytelling skills are both independent human capital inputs contributing to the success of people analytics. Furthermore, according to the research on human capital complementarities, the interconnection of employee KSAOs can produce a unique human capital complementarity that leads to higher levels of performance (Nyberg et al., 2014; Ployhart & Cragun, 2017). This study also suggests that when analytical and storytelling skills are combined, they create a complementarity interaction that leads to increased task performance (i.e., fulfilling responsibilities and completing people analytics tasks) and team performance for HR analysts (i.e., providing feasible recommendations). A sample of 173 people analytics professionals is used to test each hypothesis and illustrate the complementarity human capital relationship.

This study is timely and critically important given the increased number of organizations engaging with people analytics despite the lack of support for the KSAOs required to successfully conduct people analytics (Ellmer & Reichel, 2021; McCartney et al., 2020; Peeters et al., 2020). These questions lead to the need for this study which focuses on the direct and complementarity effect of analytical and storytelling skills in people analytics. In doing so, this study makes two theoretical contributions to the strategic human capital literature and people analytics literature. First, the study extends our understanding of human capital resources and human capital complementarities by theorizing that complementarity relationships can increase people analytics performance. Likewise, the study answers calls by Ployhart et al. (2014) and Nyberg et al. (2018), who claim that more evidence is needed to demonstrate the interconnectedness of human capital resources and their subsequent performance outputs associated with human capital resource complementarities. Second, this research investigates both the direct and complementarity effects of two sets of KSAOs (i.e., analytical and storytelling skills) on people analytics performance. Doing so responds to calls made by Ellmer and Reichel (2021), McCartney et al. (2020), and Peeters et al. (2020) for better understanding the required skills and competencies of people analytics professionals.

This paper is organized as follows. First, the literature review and hypotheses section will summarize existing research in people analytics, human capital resources, and human capital complementarities while outlining the hypotheses tested within the paper. Second, the research methodology will outline the data collection process and the profile of the study's people analytics professionals and explain the survey measures. Next, the research findings are presented, including the analysis for each hypothesis tested. Finally, the study's theoretical and practical contributions and its limitations and future research directions are discussed.

4.3 Literature Review and Hypotheses Development

4.3.1 People Analytics and Required Skills

The growing volume of data being collected by organizations coupled with the ongoing digital revolution has had a significant impact on the number of organizational functions using data to make better decisions (Caputo, Cillo, Candelo, & Liu, 2019; Fernandez & Gallardo-Gallardo, 2020; Ferraris et al., 2019; Hamilton & Sodeman, 2020; Margherita, 2020). The HR department is no exception, with many beginning to engage with workforce data to make evidence-based decisions in areas such as recruitment and selection, performance management, diversity and inclusion, and workforce planning (Hamilton & Sodeman, 2020; Harris et al., 2011; Kane, 2015; Marler & Boudreau, 2017; Rasmussen & Ulrich, 2015). This engagement with utilizing workforce data to improve decision-making has been synonymously referred to by scholars as people analytics (Green, 2017; Kane, 2015; Nielsen & McCullough, 2018; Peeters et al., 2020; Tursunbayeva et al., 2018), talent analytics (Harris et al., 2011; Sivathanu & Pillai, 2020), human capital analytics (Andersen, 2017; Boudreau & Cascio, 2017; Levenson & Fink, 2017; Minbaeva, 2018), workforce analytics (Huselid, 2018; Simón & Ferreiro, 2018), and HR analytics (Angrave et al., 2016; Aral et al., 2012; Marler & Boudreau, 2017; McCartney et al., 2020; Rasmussen & Ulrich, 2015). Despite the variation among terms, scholars agree that at its core, people analytics is focused on evidence-based decision-making that combines data, analysis, and statistical modelling to improve and support strategic human capital and organizational decisions.

Given the rise in people analytics adoption, one area that has received a significant increase in attention from researchers is the key skills required to conduct people analytics. For instance, many scholars have suggested the need for technological skills (Ellmer & Reichel, 2021; Falletta & Combs, 2020; McCartney et al., 2020; McIver et al., 2018; Pessach et al., 2020), numerical and statistical skills (Andersen, 2017; Falletta & Combs, 2020; McIver et al., 2018; Minbaeva, 2018; van der Togt & Rasmussen, 2017), data visualization skills (Andersen, 2017; McCartney et al., 2020; McIver et al., 2018), a background in social and organizational psychology (Andersen, 2017; McIver et al., 2018; van der Togt & Rasmussen, 2017), storytelling and communication (Andersen, 2017; Falletta & Combs, 2020; McCartney et al., 2020; McIver et al., 2018; Minbaeva, 2018; van der Togt & Rasmussen, 2017), and strong business acumen (Andersen, 2017; Ellmer & Reichel, 2021; McCartney et al., 2020; van der Togt & Rasmussen, 2017). Most recently, to help bring together the various viewpoints and add clarity to the HR skills debate, McCartney et al. (2020) developed a competency model outlining six distinct competencies required by HR Analysts. Their competency model argues that HR Analysts require high degrees of competence in areas such as consulting, technical knowledge, data fluency and data analysis, HR and business acumen, research and discovery, and storytelling and communication (McCartney et al., 2020).

Taken collectively, two distinct themes are emerging concerning the human capital inputs needed to perform people analytics. First, analytical skills covering technical skills, data fluency and analysis, statistical ability, and data visualization. Second, is the theme of storytelling which includes communication, storytelling, consulting, and HR and business acumen. In terms of the ability to perform people analytics tasks, several scholars have pointed to analytical and storytelling skills as a way for people analytics to add value to organizations (Andersen, 2017; Kryscynski et al., 2018; McCartney et al., 2020; McIver et al., 2018; van der Togt & Rasmussen, 2017). For instance, using data collected from 360 feedback surveys from 1,117 HR professionals, it was found that HR professionals with strong analytical ability have higher levels of job performance (Kryscynski et al., 2018). Scholars have also argued that both storytelling and analytical skills are critical in enabling HR departments to make evidence-based decisions leading to improved departmental performance (Andersen, 2017; McCartney et al., 2020; McIver et al., 2018; Minbaeva, 2018; Peeters et al., 2020).

These arguments are consistent with the beliefs of strategic human capital theory, which suggests that individual employee KSAOs can be leveraged to generate sustainable competitive advantage (Crook et al., 2011; Delery & Roumpi, 2017; Hitt et al., 2001; Wright et al., 2014). These claims are justified given the longstanding evidence supporting the relationship between human capital and performance. For example, in a meta-analysis of 66 studies conducted between 1995 and 2009, Crook, Todd, Combs, Woehr, and Ketchen (2011) found human capital was positively associated with performance (r = .17 p < .01). Furthermore, recent literature concerning strategic human capital has focused on how KSAOs can be used to gain sustainable competitive advantage through human capital resources (Barney & Felin, 2013; Crocker & Eckardt, 2014; Nyberg et al., 2014; Ployhart & Cragun, 2017; Ployhart & Moliterno, 2011; Ployhart et al., 2014). According to Ployhart et al. (2014, p. 347), human capital resources are *"individual … capacities based on individual KSAOs that are accessible for unit-relevant purposes"*. In other words, human capital resources are a specialized set of KSAO's exhibited by one individual or a collective set of KSAO's that forms a unique resource that can be used for the benefit of a particular unit (Boon, Eckardt, Lepak, & Boselie, 2018; Nyberg et al., 2014, 2018; Ployhart & Moliterno, 2011; Ployhart et al., 2014).

Within the context of people analytics and building on the arguments of human capital and human capital resources, this study argues that analytical and storytelling skills are important human capital inputs that can lead to higher levels of task and team performance. The importance of these two human capital inputs has been evidenced through several case studies (see Schiemann, Seibert, & Blankenship, 2018; Simón & Ferreiro, 2018) and examples of HR departments investing in people analytics to aid in strategic decision making. For instance, members of the people analytics team at ING, a Dutch multinational banking and financial services organization, were tasked with using their analytical skills to analyze large amounts of workforce data to systematically identify and match internal employee skill profiles best suited to fill highly skilled and specialized roles (Peeters et al., 2020). Likewise, at Google, analytical skills are being used to enhance the recruitment and selection process by developing AI and ML algorithms to predict a candidate's likelihood of success before hire (Harris et al., 2011; Shrivastava, Nagdev, & Rajesh, 2018).

In addition to analytical skills, HR departments have cited the ability to effectively communicate the return on people analytics projects and tell a data story to stakeholders as a critical skill for people analytics success (Andersen, 2017; McCartney et al., 2020; McIver et al., 2018; Minbaeva, 2018; Rasmussen & Ulrich, 2015; van der Togt & Rasmussen, 2017). For instance, Maersk Drilling uses non-technical scorecards together with storytelling to communicate powerful data stories that highlight the high-level results of the analysis to implement programs directly related to performance metrics (Rasmussen & Ulrich, 2015). Similarly, at Johnson Controls, the HR department places a high priority on storytelling and the ability to translate complex insights into a common business language to achieve buy-in from managers and implement changes focused on improving business outcomes (McIver et al., 2018).

Considering the arguments of strategic human capital theory and the examples above demonstrating the influence of analytical and storytelling skills on people analytics, this study hypothesizes:

H1: Analytical (1a) and storytelling skills (1b) are positively associated with individual HR Analyst task performance.

H2: Analytical (2a) and storytelling skills (2b) are positively associated with people analytics team performance.

4.3.2 Human Capital Resource Complementarities

Strategic human capital resource literature has focused significantly on understanding how individual KSAOs are independently expected to improve performance and generate sustainable competitive advantage (Boon et al., 2018; Nyberg et al., 2018; Ployhart & Cragun, 2017; Ployhart et al., 2014). However, in addition to the linear effect of human capital inputs on value creation, human capital resource scholars have begun to theorize that individual KSAOs may be bundled or combined to offer increased levels of performance and competitive advantage (Devaraj & Jiang, 2019; Fulmer & Ployhart, 2014; Humphrey, Morgeson, & Mannor, 2009; Ilgen, Hollenbeck, Johnson, & Jundt, 2005; Ployhart et al., 2014). For example, human capital resource complementarities can occur when different human capital inputs (i.e. KSAOs) combine interactively to produce greater value together than apart (Adegbesan, 2009; Brymer & Hitt, 2019; Ployhart & Cragun, 2017; Ployhart et al., 2014).

To emphasize how the KSAOs of one individual can be combined to generate super-additive performance outcomes, strategic management scholars have drawn on the KSAOs of star performers in professional sports to better understand and highlight this relationship (Call, Nyberg, & Thatcher, 2015; Crocker & Eckardt, 2014; Nyberg et al., 2014; Taylor & Bendickson, 2021; Wolfson & Mathieu, 2018). For example, in a study conducted with 169 cyclists competing in the Tour De France, it was found that the skills of sprinting and mountain climbing complemented each other, accounting for higher individual-level performance throughout the stages of the race (Wolfson & Mathieu, 2018). Given the task demands of people analytics and the need to analyze and translate workforce data into meaningful insights, this study argues that a similar interaction exists where analytical and storytelling skills complement each other leading to higher performance. For instance, if the insights gained through people analytics cannot be turned into a compelling data story that motivates change, the analysis conducted is of no use. Similarly, if an employee can build and present a data story but cannot undertake sufficient analysis, the story will be ineffective and will not motivate change. In other words, for people analytics to provide practical insights, it requires the combined effect of analytical and storytelling skills. Therefore, we hypothesize:

H3: A complementarity effect between individual analytical and storytelling skills exists and is associated with (3a) HR Analyst task performance and (3b) people analytics team performance.

4.4 Methodology

4.4.1 Data Collection and Sample Profile

To test the hypotheses stated above, data was collected via an online survey focused on the underlying theme of people analytics skills and competencies. To ensure the face validity of the survey and clarity of the survey measures used, the survey was pilot-tested among a group of People Analysts and People Analytics Managers. These individuals were selected as they are responsible for the day-to-day responsibilities of people analytics tasks and the development and management of the people analytics function within their organizations. As a result, questions were revised slightly, including rephrasing some questions for clarity and reordering items.

Once face validity had been achieved, the survey was sent through LinkedIn messages to members of the author's network who work in people analytics. A total of 555 invitations to participate were distributed between December 1, 2020, and April 30, 2021, with two reminders sent out to help increase participation. Overall, a total of 241 responses were received, generating a response rate of 43%. To further increase the number of participants and reach of the survey, it was then posted on several people analytics and HR LinkedIn groups, including *People Analytics Community, People Analytics: Data-Driven HR, HR Analytics Ireland, and HR Professionals Europe,* as well as the author's personal LinkedIn page. This resulted in an additional 63 responses, bringing the total responses to 304. After removing incomplete responses, the total sample size is 173 respondents.

Among the participants, 58% were male and 42% female, with 49% of respondents holding People Analyst roles with the remaining 51% holding higher-level positions such as

Manager/Lead People Analytics (24%), Senior Manager People Analytics (5%), Director People Analytics (9%), and Head of People Analytics (13%). Concerning the age profile of the respondents, 31% of respondents were under 30 years old, 46% were between the ages of 30 and 40, 21% were between the ages of 41 and 50, and 2% being between the ages of 51 and 60. Most respondents (58.5%) reported having a Master's Degree, of which 68% being in the subject area of business, human resource management, and economics (46%) and psychology/industrial psychology (22%). Concerning the geographic location of participants, 79% were from either North America (47%) or Europe (32%), with the remainder in countries in Asia (13%), South America (5%), Africa (2%), and Australia/Oceania (2%). The average working experience of respondents was eight years (SD = 6.4).

4.4.2 Measures

Analytical and storytelling skills. Although people analytics has garnered increased attention over the past several years, scales used to operationalize analytical and storytelling skills among people analytics are scarce. As such, this paper draws on three influential papers, Minbaeva (2018), Davenport and Kim (2013), and Boldosova (2020), where each paper presents items representing the key skills and sample questions to help measure analytical and storytelling skills.

Based on the work of Minbaeva (2018), six items were developed to measure analytical skills. Respondents were asked to describe the extent to which they agreed on these items related to their analytical skills using a five-point Likert-type scale, varying from 1 = strongly disagree to 5 = strongly agree. They were: "I have the analytical skills needed to understand and satisfy business demands for people analytics", "I have the skills needed to produce key metrics", "I have the analytical skills needed to run statistical models", "I can derive analytical models that can help answer business questions", "I can use statistical software packages (e.g., Excel, SPSS, PowerBI, R, Stata, or Tableau) to analyze data", and "I can use our digital HR packages (e.g., SAP Success Factors, Workday, Oracle HCM) to analyze data".

Exploratory factor analysis (EFA) with a principal axis factoring extraction method and oblique rotation technique was conducted to determine the factor structure of the measure. One factor structure was revealed with all factor loadings above .58 except for the item the digital HR package (.40). Considering that not all organizations will have sophisticated digital HR packages and low factor loading, this item was dropped. The reliability was assessed for the five remaining items, showing a Cronbach's alpha of .80.

Similarly, nine items were developed based on the conceptual work by Minbaeva (2018), Davenport and Kim (2013), and Boldosova (2020). Respondents were asked to describe the extent to which they agreed on items related to their ability to tell a data story using a five-point Likert-type scale, varying from 1 = strongly disagree to 5 = strongly agree. These items included "I can easily 'tell a story' from data", "I can communicate results in a way that makes them comprehensible for business purposes, "I can visualize results for communication purposes", "I can communicate the impact of data on business performance", "The findings that I present are understood by our stakeholders", "Our stakeholders can draw managerial implications from the results that I present", "I can frame a problem relevant to our business needs", "I can interpret findings using business language" and "I can use storytelling to influence decision-makers". The results from EFA with a principal axis factoring extraction method and oblique rotation technique revealed that all nine items loaded on one factor with all factor loadings above .58. Additionally, the reliability was assessed, showing a Cronbach's alpha of .88. Next, CFA was performed for analytical and storytelling skills along with other key variables in this study. The CFA results are reported below in the sub-section assessing common method bias.

Task performance. Five items were adopted from Podsakoff and Mackenzie (1989). Respondents were asked to describe the extent to which they agreed on items related to their ability to meet job requirements and complete tasks on a five-point Likert-type scale, varying from 1 = strongly disagree to 5 = strongly agree. Example items include “I meet all the formal performance requirements of the job” and “I fulfil all responsibilities required by my job”. The reliability was assessed, showing a Cronbach's alpha of .80

Team performance Three Items were adopted from Marrone, Tesluk, and Carson (2007). Example items included “we meet specified project deadlines in a timely manner”, “we provide recommendations that are feasible (i.e., can realistically be implemented),” and “we successfully manage project-related challenges or obstacles as they occur”. Each item was measured using a five-point Likert-type scale, varying from 1 = strongly disagree to 5 = strongly agree. The reliability was assessed, showing a Cronbach's alpha of .78.

Control variables Individual variables including gender, age, level of education, and work experience were controlled for given their potential to influence analytical and storytelling skills. Gender was measured using three categories (1 = Male, 2 = Female, 3 = Other or prefer not to answer). Age was measured via 5 classifications (1 = less than 30 years old, 2 = 30-40 years old, 3 = 41-50 years old, 4 = 51-60 years old, 5 = 60 years and older). Level of education was measured by four categories (1 = No formal education/qualification, 2 = Bachelor’s Degree, 3 = Master’s Degree, 4 = Doctoral/PhD). The variable of work experience was measured by years.

Table 4.1 Fit Statistics from Measurement Model Comparison

Models	*χ²/df*	*CFI*	*TLI*	*RMSEA*	*SRMR*	*Δχ2*	*Δdf*
Full measurement model	**269.99/201**	**.96**	**.95**	**.04**	**.06**		
Model A[a]	423.30/204	.87	.85	.08	.08	153.31***	3
Model B[b]	639.02/206	.73	.70	.11	.11	369.03***	5
Model C[c]	404.41/204	.87	.86	.08	.09	134.42***	3
Model D[d] (Harman's Single Factor Test)	735.48/207	.67	.63	.12	.11	465.49***	6

Notes: N = 173, ***p <.001; χ^2=chi-square discrepancy, df=degrees of freedom; CFI=Comparative Fit Index; TLI= Tucker-Lewis Index; RMSEA=Root Mean Square Error of Approximation; SRMR= Standardized Root Mean Square Residual; =difference in chi-square, =difference in degrees of freedom. In all measurement models, error terms were free to covary to improve fit and help reduce bias in the estimated parameter values. All models are compared to the full measurement model

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[a] = Analytical skills and storytelling skills combined into a single factor.

[b] = Analytical skills, storytelling skills, and HR Analyst task performance combined into a single factor.

[c] = HR Analyst task performance and people analytics team performance combined into one factor.

[d]=All factors combined into a single factor.

4.4.3 Common Method Bias

CFA was performed to establish the discriminant validity of the scales used in the survey and to assess the degree of common method bias present in the data. A full measurement model was tested with analytical skills, storytelling skills, HR Analyst task performance, and people analytics team performance being loaded onto their own factors. According to the cut-off criteria for fit indexes (Hu & Bentler, 1999), the four-factor model showed a good model fit (χ^2/df = 269.99/201 = 1.28, p < .001; Comparative Fit Index (CFI) = .96; Tucker-Lewis Index (TLI) = .95; root-mean-square error of approiximation (RMSEA) = .04; standardized root-mean-square residual (SRMR) = .06) with a X^2/df values less than 3, a CFI value greater than .95, RMSEA less than .08, and an SRMR of less than .08.

Four subsequent χ^2 difference tests were then performed to compare the full measurement model to alternative nested models. As shown in Table 4.1, the comparison results reveal that the model fit of the full measurement model was significantly better than the alternative models (all at p <.001), suggesting that the study's variables are distinct and ruling out concerns of common method bias.

Table 4.2 presents the descriptive statistics of the core variables in this study, including the mean, standard deviation, and correlations.

Table 4.2 Descriptive Statistics and Correlations of Study Variables

Variables	**Mean**	**SD**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1. HR Analyst Task Performance	4.26	.58							
2. People Analytics Team Performance	4.13	.56	.34**						
3. Analytical Skills	4.34	.49	.18*	.38**					
4. Storytelling Skills	4.29	.51	.28**	.36**	.48**				
5. Gender	.58	.49	-.11	-.07	.06	-.06			
6. Age	1.93	.76	-.12	.10	-.01	.14	.11		
7. Level of Education	2.79	.73	-.11	-.04	.05	.04	.08	-.05	
8. Work Experience	8.85	6.52	.04	.01	-.11	.10	.01	.67**	-.09

Notes: N = 156 (Listwise), ** p<.05, * p<.10, All tests were two-tailed.

Due to the small sample size (173) and the large number of items (22) along with control variables, structural equation modelling (SEM) was not deemed as an appropriate method for data analysis. As such, hierarchical linear modelling was used to test the hypotheses proposed in this study. The results from the analysis can be found in Table 4.3. To assess the potential for multicollinearity and autocorrelation among variables, variance inflation factors (VIF) and the Durbin-Watson test were calculated. The values of the average VIF ranged from 1.02 to 1.93, each less than the threshold of 5 suggested by Haan (2002) indicating no concerns for multicollinearity. Likewise, results of the Durbin-Watson test showed no concern for the autocorrelation with a result of 1.79 for HR Analyst task performance and 1.94 for people analytics team performance falling within acceptable limits of between 1.0 and 3.0 (Field, 2009).

Hypothesis 1 proposed that analytical skills (1a) and storytelling skills (1b) would be positively associated with HR Analyst task performance. Results in Table 4.3 show that the standardized coefficient of analytical skills on HR Analyst task performance was positive but not significant ($\beta = .07$, *n.s.*). In contrast, the standardized coefficient of storytelling skills on HR Analyst task performance was positive and significant ($\beta = .24$, $p < .01$). Therefore, the study finds partial support for Hypothesis 1, where Hypothesis 1b was supported.

Hypothesis 2 proposed that analytical skills (2a) and storytelling skills (2b) would be positively associated with people analytics team performance. Results in Table 4.3 show that the standardized coefficient of analytical skills on people analytics team performance was positive and significant ($\beta = .27$, $p < .01$). Likewise, the standardized coefficient of storytelling skills on people analytics team performance was positive and significant ($\beta = .22$, $p < .05$). Therefore, the study finds support for hypothesis 2.

Hypothesis 3a proposed that a complementarity effect between individual analytical and storytelling skills exists and is positively associated with HR Analyst task performance.

Table 4.3 Hierarchical Linear Regression Analysis

Variable	HR Analyst task performance			People analytics team performance		
	Step 1	Step 2	Step 3	Step 1	Step 2	Step 3
Control						
Gender	-.124	-.110	-.108	-.092	-.089	-.087
Age	.196	.157	.193	.180	.124	.162
Education	-.100	-.115	-.106	-.034	-.055	-.046
Work experience	-.099	-.091	-.109	-.112	-.069	-.088
Predictors						
Analytical skills		.071	.062		.273**	.264**
Storytelling skills		.236**	.251**		.221*	.238**
Moderator						
Analytical skills * storytelling skills			.176*			.188*
Adjusted R^2	.019	.084	.109	-.002	.172	.202
ΔR^2	.044	.076	.030	.024	.179	.034
ΔF	1.74	6.39**	5.22*	.94	16.78***	6.64**

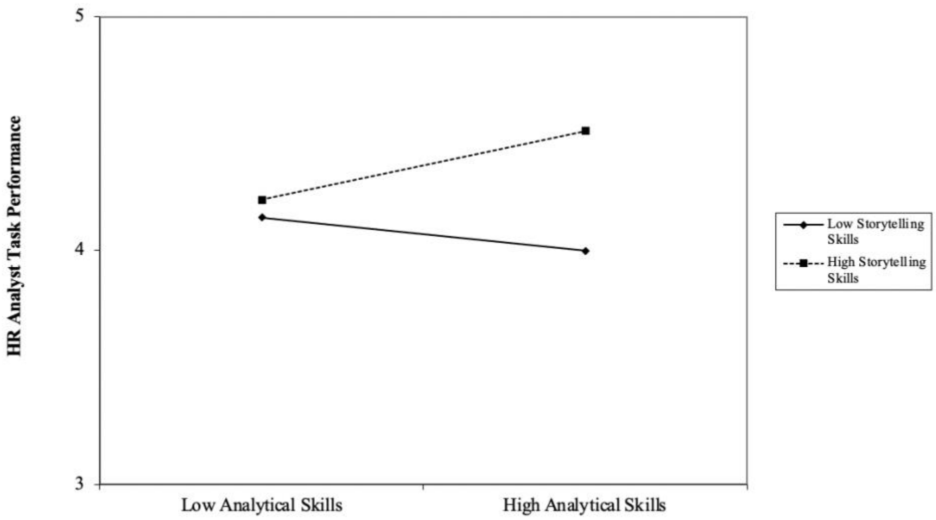
Note: Standardized coefficients were reported. Listwise deletion method was employed to deal with missing data in hierarchical multiple regression analysis, which reduced the sample size from 173 to 156.
** p<.01, * p<.05, All tests were two-tailed.

To test for moderation, recommendations by Aiken, West, and Reno (1991) were followed, where each variable in the analysis was standardized. The moderation results in Table 4.3 show that the standardized coefficient of the interaction term between analytical skills and storytelling skills was significantly associated with HR Analyst task performance ($\beta = .18$, $p < .05$), accounting for a positive 3% change in the R^2 value and an F change of 5.22, $p < .05$.

The interaction plot of analytical and storytelling skills on HR Analyst task performance is presented in Figure 4.1. In addition, a simple slope analysis was conducted to estimate the slopes for the links between analytical skills and HR Analyst task performance under both high and low levels of storytelling skills. The simple slope analysis revealed that when storytelling skills are high (one SD above the mean), the slope was .15 ($t = 2.09$, $p < .05$). When storytelling skills are low (one SD below the mean), the slope was -.07 ($t = -.96$, *n.s.*). Overall, the results show that storytelling skills strengthen the impact of analytical skills on HR Analyst task performance. Therefore, Hypothesis 3a was supported.

Figure 4.1 Interaction between Analytical Skills and Storytelling Skills on

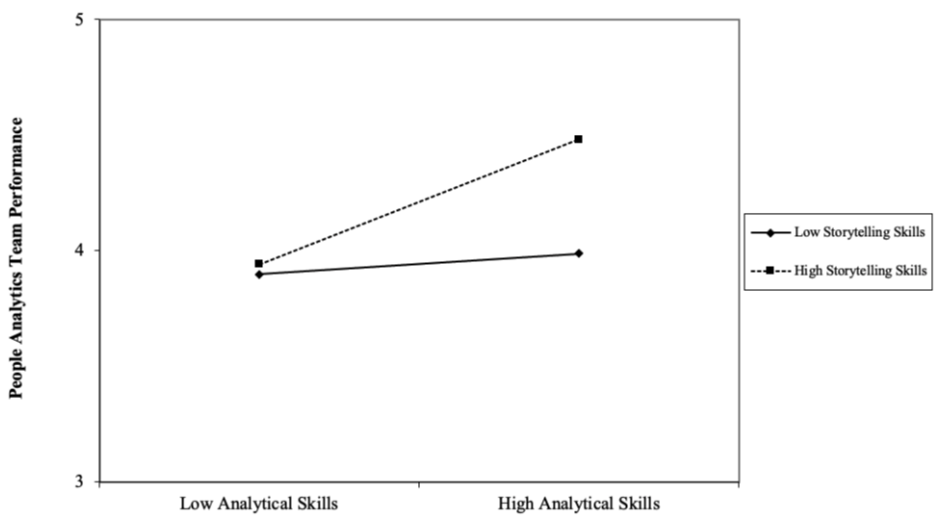
HR Analyst Task Performance



Hypothesis 3b proposed that a complementarity effect between individual analytical and storytelling skills would exist and is positively associated with people analytics team performance. Again, recommendations by Aiken et al. (1991) were followed where each variable in the analysis was standardized. The moderation results in Table 4.3 show that the standardized coefficient of the interaction term between analytical skills and storytelling skills was significantly associated with people analytics team performance (β = .19, p < .05), accounting for a positive 3.4% change in the R^2 value and an F change of 6.64, p < .05. The interaction plot of analytical skills and storytelling skills on HR Analyst team performance is presented in Figure 4.2. In addition, a simple slope analysis was conducted to estimate the slopes for the links between analytical skills and people analytics team performance under both high and low levels of storytelling skills. The simple slope analysis revealed that when storytelling skills are high (one SD above the mean), the slope was .27 (t = 4.17, p < .001). When storytelling skills are low (one SD below the mean), the slope was .04 (t = .65, *n.s.*). Overall, the results show that storytelling skills strengthen the impact of analytical skills on HR Analyst team performance. Therefore, Hypothesis 3b was supported.

Figure 4.2 Interaction between Analytical and Storytelling Skills on

People Analytics Team Performance



4.5 Discussion

This study aimed to investigate how analytical and storytelling skills affect people analytics performance. Drawing on the human capital resource framework and the human capital complementarity literature, this study theorized both direct and complementarity effects of analytical and storytelling skills on people analytics performance, including HR Analyst task performance and people analytics team performance. Using data collected from people analytics professionals, support was found for the direct impact of analytical skills on team performance but not for individual HR Analyst task performance. Storytelling skills were positively associated with HR Analyst task performance and people analytics team performance. In addition, a complementarity effect was found where storytelling skills strengthened the positive impact of analytical skills on HR Analyst task performance and team performance. Implications for research and practices are discussed.

4.5.1 Theoretical Contributions

The findings of this study make two significant contributions to the fields of people analytics and strategic human capital. First, the study responds to several calls for research investigating the KSAOs that are most influential with regards to people analytics performance (Andersen, 2017; Ellmer & Reichel, 2021; Huselid, 2018; McCartney et al., 2020; McIver et al., 2018; Minbaeva, 2018; Peeters et al., 2020). For instance, although scholars have identified various KSAOs as critical to the success of people analytics, researchers have yet to adequately resolve this gap by empirically examining the significance of specific KSAOs and linking them to people analytics results. As such, the study examines the direct effect of two human capital inputs (i.e., analytical and storytelling skills) on individual and team people analytics performance, finding mixed results. In particular, the study finds that analytical skills were only significant in improving team performance rather than the HR Analyst task performance. The unsupported relationship between analytical skills and individual HR Analyst task performance appears to be counterintuitive at first glance, however, it is an important finding suggesting analytical skills alone are not sufficient concerning individual people analytics performance.

Furthermore, storytelling skills were significant and positively associated HR Analyst task and team performance. This finding is consistent with previous claims made by scholars concerning the importance of storytelling skills (Andersen, 2017; Falletta & Combs, 2020; McCartney et al., 2020; McIver et al., 2018; Minbaeva, 2018). For instance, Minbaeva (2018) proposed that people analytics professionals must convey insights to data consumers in HR and business language. Likewise, McCartney et al. (2020) suggested that a critical competency required of people analytics practitioners is the ability to interpret and frame insights extracted from workforce data into a compelling narrative. These findings of the performance impact of storytelling skills provide strong evidence for these arguments.

Second, the study extends the current understanding of the impact of human capital and human capital complementarities on performance. Until now, the focus of human capital resources has been on exploring how one human capital resource can affect performance rather than how several human capital resources or KSAOs can be combined or bundled to influence performance (Ployhart et al., 2014). Likewise, evidence demonstrating how different human capital inputs interact to create super-additive value remains needed (Nyberg et al., 2018; Ployhart & Cragun, 2017; Ployhart et al., 2014). As such, this study answers these calls, offering insight into how complementarity relationships between individual KSAOs lead to higher levels of performance. For example, consistent with the theory of human capital complementarities, the findings suggested that analytical skills and storytelling skills create a synergistic relationship that enhances the value of each KSAO. In particular, storytelling skills moderate the relationships between analytical skills with HR Analyst task performance and team performance, where the relationships are stronger when storytelling skills are high. Analytical skills did not associate with HR Analyst task performance on their own. It is only when combined with storytelling skills, analytical skills can directly improve HR Analyst task performance.

4.5.2 Practical Implications

The results indicate that both storytelling and analytical skills are important in performing people analytics. For example, from an analytics perspective, HR Analysts need to have the skills to produce key metrics and run statistical models using various software packages (e.g., Excel, SPSS, PowerBI, R, Stata, or Tableau). In contrast, HR Analysts require storytelling skills which represents the ability to effectively communicate and visualize the impact of data on business performance to influence decision-making. Likewise, the findings suggest that a complementarity relationship exists between analytical and storytelling skills where, when combined, they offer superior performance. As such, HR departments should concentrate on building their people analytics resource around HR Analysts who have high levels of analytical and storytelling skills so that they can analyze, interpret, and translate insights into a compelling data story.

From a broader standpoint, the findings also offer valuable insight for HR departments looking to begin or have just started their people analytics journey. For instance, storytelling skills were positively associated with individual people analytics task and team performance, while analytical skills were only found to be significant in team performance. This means that if HR departments want to invest in people analytics or are just getting started, it is important to build storytelling capabilities first, as this will provide the most benefit in the short term. Subsequently, HR departments can concentrate on developing their analytical skills in order to take advantage of the complementarity relationship between analytical and storytelling skills. In other words, when developing people analytics capabilities, hire storytelling skills and train analytical skills.

4.5.3 Limitations and Future Research

Despite the study offering significant insight into theory and practice in strategic human capital and people analytics, it is not without its limitations. First, the study's cross-sectional research design does not allow for determining causality and only represents one point in time. As a result, future research is encouraged to address this by collecting longitudinal data on people analytics professionals. These studies would yield interesting results as the field continues to evolve, given the rapid adoption of pre-built human capital systems capable of performing AI and ML. This evolution raises the questions, to what degree will analytical skills be relevant for employees in people analytics roles if this will be the primary responsibility of AI moving forward? And how can human capital complement this new form of digital capital? This relationship between employees and AI is a significant area of future research blending strategic management, human resources, and organizational behaviour.

Second, this study is limited in its small sample size. Future research is encouraged to collect larger samples specifically in geographical areas underrepresented in this study, such as Asia, South America, Africa, and Australia/Oceania, to help determine causality among variables and add to the generalizability of the study's findings. Third, given time constraints and generally small team sizes, it was difficult to obtain multiple team member responses. As such, an individual self-report was used to represent the people analytics team performance variable. To address this limitation of the research design, future research should concentrate on gathering responses from larger people analytics teams and obtain multiple team member responses and aggregate them increasing the reliability and validity of the people analytics team performance construct.

This study also sets the foundation for further research that blends strategic human capital and human capital resources with people analytics. First, one avenue for future research would be to investigate the link between human capital resources and organizational outcomes through people analytics. This would meet various calls within the people analytics literature (Marler & Boudreau, 2017; McCartney et al., 2020) and the strategic management literature (Eckardt, Crocker, & Tsai, 2020; Ployhart & Chen, 2019) to better understand how people analytics and teams can create value for organizations. For example, researchers could focus on understanding how cross-level human capital resource complementarities emerge and how different variations in these complementarities can impact people analytics and organizational performance.

Second, although the results support the complementarity effects of analytical and storytelling skills, finding one individual with both sets of KSAOs required to perform people analytics tasks is unlikely (Huselid, 2018). To that end, future research is encouraged to investigate how unit-level human capital resources (i.e., people analytics teams) can combine to create sustainable competitive advantage. For example, considering that human capital resources represent a collective set of KSAOs that form a unique unit-level resource, it is possible that two independent human capital resources can create a within-level interaction at the team level (Crocker & Eckardt, 2014; Ployhart et al., 2014; Soda & Furlotti, 2017; Wolfson & Mathieu, 2018). Within the context of people analytics, the same relationship may exist where a people analytics team is made up of two highly specialized human capital resources (i.e., analytical and storytelling) and interact, generating an output more significant than if they were used independently. This line of questioning also offers another direction for future research, which is to draw on team composition theory or complex adaptive systems theory to better illustrate how the structure of people analytics teams and their interconnected roles complement each other to produce super-additive value to organizations.

Finally, future research should investigate whether people analytics can be used from the perspective of causal complementarities. In other words, can a people analytics human capital resource be leveraged to help develop and acquire other human capital resources across an organization? This causal relationship is not new and has been indirectly referred to by several case studies exploring how analytical skills can be used to develop and run AI and ML programs to effectively inform decision making in areas such as talent management, and training and development (Garg et al., 2021; Pessach et al., 2020; Sivathanu & Pillai, 2020). However, academic inquiry has not centred on this relationship in this way, and the causal complementarity effect of human capital remains neglected within the existing human capital literature (Ennen & Richter, 2010; Fulmer & Ployhart, 2014; Maritan & Peteraf, 2011).

4.6 Conclusion

With the right skills, people analytics will enable organizations to make faster and better decisions. This study provides valuable insights on both the direct and complementarity effects of analytical and storytelling skills on individual and team performance. It serves as a starting point to unlock the puzzle of how human capital can influence people analytics performance. Future research is encouraged to further discover and develop key KSAOs of HR professionals to fully leverage the power of data and analytics.

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Chapter 5 Study 3 – Bridging the Gap: Why, How, and When People Analytics can Impact Organizational Performance

5.1 Abstract

Purpose – Despite the growth and adoption of people analytics, it remains unknown whether people analytics can impact organizational performance. As such, this study aims to address this important issue by understanding why, how, and when people analytics leads to increased organizational performance and uncover the mechanisms through which this increased performance occurs.

Design/methodology/approach – Using data collected from 155 Irish organizations, structural equation modeling was performed to test the integrated model linking HR technology, people analytics, EBM, and organizational performance.

Findings – The paper's findings support the proposed moderated mediation model, suggesting that people analytics positively impacts organizational performance through its EBM capability. Further, the results indicate that HR technology enables people analytics and strengthens the impact of people analytics on EBM.

Originality/value – By theorizing and identifying EBM as a mediator between people analytics and organizational performance, this study extends our understanding of why and how people analytics leads to higher organizational performance. Additionally, this study addresses the conditional effect of HR technology in enabling people analytics and moderating the link between people analytics and EBM. Finally, this study contributes to people analytics research by revealing and investigating people analytics' performance impact on the underlying mechanism (EBM) and boundary conditions (HR technology).

Keywords: *People Analytics, Human Resource (HR) Analytics, Evidence-Based Management, Organizational Performance, Human Resource Management*

5.2 Introduction

The concept and application of big data has seen increasing attention as researchers and professionals aim to understand how data can be transformed into actionable insights leading to improved organizational performance (Chierici et al., 2019; Ferraris et al., 2019; Santoro et al., 2019; Singh & Del Giudice, 2019). Consequently, this interest has transcended various management disciplines including HRM (Fernandez & Gallardo-Gallardo, 2020; Marler & Boudreau, 2017; McCartney et al., 2020). For instance, people analytics is projected to be a "game-changer" for the future of HR (van der Togt and Rasmussen, 2017, p. 131), offering the capabilities to utilize the growing availability of workforce data to make evidence-based decisions (Garcia-Arroyo & Osca, 2019; King, 2016; Marler & Boudreau, 2017; McIver et al., 2018; Sharma & Sharma, 2017; Sivarajah et al., 2017). For example, through the analysis of candidate and employee data, Google's people analytics team has developed an evidence-based approach to improve its recruitment and selection process by identifying several elements of high performance that could predict a candidate's likelihood of success (Harris et al., 2011; Shrivastava et al., 2018). Similarly, in addition to recruitment and selection, people analytics offers organizations the ability to address various other HR challenges, including employee engagement, diversity & inclusion, and turnover (Andersen, 2017; Buttner & Tullar, 2018; Harris et al., 2011; Levenson, 2018; Simón & Ferreiro, 2018).

To date, the extant people analytics literature has focused on many areas, including the current limitations and challenges facing the development of people analytics (Boudreau & Cascio, 2017; Huselid, 2018; Jeske & Calvard, 2020; Levenson & Fink, 2017; Minbaeva, 2018), best practices in developing and utilizing people analytics (Falletta & Combs, 2020; Green, 2017), and the impact and importance of analytical skills (Kryscynski et al., 2018; McCartney et al., 2020). Likewise, professional associations, including CIPD and consulting firms such as Deloitte, have begun to publish white papers and reports claiming the benefits of leveraging “people data” to make data-driven decisions (CIPD & WorkDay, 2018; Deloitte, 2017, 2018; McCartney et al., 2020). Despite these claims and case studies, research investigating how and to what extent people analytics impacts and influences organizational performance remains scarce (Huselid, 2018; Minbaeva, 2018). On this basis, this study seeks to understand how and why people analytics influences organizational performance and uncover the mechanisms through which this increased performance occurs.

This study draws on the resource-based view of the firm (Barney, 1991) to suggest that people analytics are a valuable, rare, difficult to imitate, and non-substitutable resource. This argument is justified as people analytics acquires and translates high-quality workforce data into information, resulting in key organizational insights (Marler & Boudreau, 2017; Minbaeva, 2018). For example, according to Minbaeva's (2018) human capital analytics framework, people analytics requires three distinct elements: high-quality data, analytical competency, and the strategic ability to act to produce information and insights needed to make data-driven decisions. Taken together, high-quality data, analytical competency, and the strategic ability to act are valuable and firm-specific resources, offering organizations insight into key issues facing their workforce. Nevertheless, having this resource is not enough to generate organizational success; instead, organizations must appropriately exploit and deploy these resources to achieve organizational success (Lin & Wu, 2014; Teece et al., 1997; Wu, 2010). As such, this study also draws upon dynamic capabilities to demonstrate how organizations deploy the insights gained from people analytics to achieve competitive advantage (Teece et al., 1997; Winter, 2003). To do so, this study adopts EBM (Bezzina et al., 2017; Rousseau & Barends, 2011) to represent this dynamic capability. Likewise, this study proposes that HR technology will enhance people analytics’ impact on EBM, leading to higher organizational performance.

By theorizing and identifying EBM as a mediator between people analytics and organizational performance, this study extends our understanding of why and how people analytics leads to higher organizational performance. Thus, providing a solid foundation for the strategic importance of people analytics. Additionally, this study addresses the conditional effect of HR technology in enabling people analytics and moderating the link between people analytics and EBM. Finally, this study contributes to people analytics research by revealing and investigating people analytics' performance impact on the underlying mechanism (EBM) and boundary conditions (HR technology).

This paper's subsequent sections are structured as follows: First, the literature review and hypotheses section will summarize existing research in people analytics while outlining the four hypotheses tested within the paper. Second, the research methodology will describe the data collection process and offer a detailed explanation of the survey measures. Third, the research findings are presented, providing analysis and support for each of the hypotheses tested. Lastly, the paper's theoretical contributions to people analytics and EBM are presented, implications for practice, limitations, and areas for future research are discussed.

5.3 Literature Review and Hypotheses Development

5.3.1 Linking People Analytics to Organizational Performance: A Resource-Based View

Consistency exists in both academia and practice for the strategic importance of people analytics; however, there is still much debate on both sides as to what people analytics actually is, since a clear and conceptual definition has yet to be established (Falletta & Combs, 2020; Fernandez & Gallardo-Gallardo, 2020; McCartney et al., 2020). For example, according to Marler and Boudreau (2017, p. 15), people analytics is *"[a]n 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*". Similarly, CIPD (2019) claim that people analytics is an analytical process used to solve business problems, suggesting that it enables HR professionals to gain insight into HR policies and processes, which can be used to make evidence-based workforce decisions. Likewise, various consulting firms and professional associations have claimed that people analytics is not one-dimensional but instead falls along a spectrum where the maturity of the people analytics function will determine the level of analytics that can be conducted (CIPD, 2019; Deloitte, 2013). For example, Deloitte (2013) claim that people analytics can be classified into four distinct levels; operational reporting, advanced reporting, advanced analytics, and predictive analytics. More recently, CIPD (2019) built upon this premise, suggesting that people analytics operates on five levels: operational, descriptive, diagnostic, predictive, and prescriptive.

Considering the various viewpoints and drawing upon several definitions from the extant literature, this paper defines people analytics as the progressive process of transforming and translating high-quality workforce data into organizational insights, enabling managers to make informed and data-driven workforce decisions. People analytics is defined in this way as it offers a holistic perspective of the concept considering the people analytics process from the start (incorporating the translation and transformation of data) to finish (generating organizational insights). Second, the chosen definition addresses the various levels or stages along the people analytics maturity spectrum, which is not discussed in the current definitions presented in the extant literature.

In light of this definition, this paper operationalizes people analytics through the adoption of the human capital analytics framework (Minbaeva 2018), where people analytics comprises of three dimensions: high-quality data, analytical competence, and strategic ability to act. High-quality data suggests that the data used for analytics needs to be accurate, consistent, timely, and complete. For instance, organizations need to ensure that the data being used to conduct people analytics is accurate. Without accurate data, the insights gained from the analytics will be unreliable and offer no benefit to the organization (Fosso Wamba, Akter, Trinchera, & De Bourmont, 2019; Minbaeva, 2018; Peeters et al., 2020). Alternatively, inaccurate data could lead to implementing solutions that do not address the business's actual challenges. In addition, people analytics requires a high degree of analytical competence, referring to the analytics team's ability to apply statistical analysis and techniques to workforce data to transform data into valuable insights (McCartney et al., 2020). For example, the analytics team needs to frame relevant research questions and answer them through developing causal models and performing sophisticated statistical analysis (Minbaeva, 2018). Moreover, the team needs to translate the insights gained into a compelling analytics narrative or story (Andersen, 2017; McCartney et al., 2020; Minbaeva, 2018). Lastly, the strategic ability to act refers to having the required managerial support to implement solutions based on the data, information, and insight gathered from people analytics.

Building on the above notion, this paper argues that people analytics contributes to organizational performance by transforming and translating high-quality workforce data into organizational insights. Likewise, people analytics (i.e., high-quality data, analytical competency, and strategic ability to act) can be viewed as an organizational resource offering competitive advantage (Barney, 1991). According to the resource-based view of the firm, competitive advantage is derived from resources found within organizations that can be characterized as valuable, rare, difficult to imitate, and are non-substitutable (Barney, 1991; Sirmon et al., 2011, 2007; Wright et al., 2001). As such, this paper argues that people analytics are valuable to organizations as they allow HR to identify and address workforce challenges using organizational facts. For example, according to McIver et al. (2018), dashboards are an efficient way of visualizing people analytics and providing the information necessary to inform workforce decision-making. Moreover, Kryscynski et al. (2018) suggests that people analytics offers both managers and executives empirical evidence to make well-informed decisions about the workforce.

Additionally, the paper suggests that people analytics are rare as several scholars have described people analytics in organizations as being underdeveloped and lacking a high level of maturity (Andersen, 2017; Angrave et al., 2016; Green, 2017; King, 2016; Levenson & Fink, 2017; Minbaeva, 2018). For example, many organizations struggle to utilize the workforce data that they have access to, with very few progressing past basic reporting and offering only descriptive statistics (i.e. headcount, demographic information, and turnover rates) (Andersen, 2017; Angrave et al., 2016; Green, 2017; King, 2016; Levenson & Fink, 2017; Minbaeva, 2018). According to Levenson and Fink (2017), organizations struggle to develop past basic reporting since HR cannot create predictive models and cannot provide the necessary forward-looking analysis required of people analytics. Furthermore, Andersen (2017) claims that the lack of people analytics maturity in organizations can also be attributed to low levels of HR technology, poor data quality, few resources, lack of analytical competencies, and a lack of buy-in from senior management.

To that effect, this study also argues that people analytics are currently difficult to imitate. To utilize and conduct value-adding people analytics effectively, organizations need to have high-quality data, the analytical capabilities, and the strategic ability to act. Without all three, it is difficult to achieve. For example, it would be ineffective to have the analytical capabilities without high-quality data as the models and analysis would be based on inaccurate data. Similarly, it is not helpful to have high-quality data but to lack the analytical skills to transfer the data into actionable insight. Likewise, suppose HR departments have high-quality data and the analytical capabilities, however, they do not have managerial buy-in and cannot act on the insights and findings. In that case, people analytics will not influence or drive change. Lastly, since no other HR policy or practice can offer the same information, people analytics is non-substitutable. Additionally, the data, information and insights generated from one organization's workforce data would be unique and relevant to its own people and business-related issues. Such a resource is difficult to replace.

Based on the above, people analytics is a valuable, rare, difficult to imitate, and non-substitutable resource that can generate competitive advantage. Therefore, it is hypothesized:

Hypothesis 1: People analytics is positively associated with organizational performance.

5.3.2 The Mediating Role of EBM

People analytics provides organizations with the data, information, and insights required to build competitive advantage (Huselid, 2018; Minbaeva, 2018). However, to generate a competitive advantage, these resources alone are not enough. Organizations must also deploy and utilize the resources effectively (Fu et al., 2017; Lin & Wu, 2014; Sirmon et al., 2007). This idea is consistent with dynamic capabilities, which suggests that competitive advantage depends on an organization's capacity to successfully incorporate, develop, and reconfigure resources (Teece et al., 1997). Numerous research studies have identified several competencies to study dynamic organizational capabilities, including innovative capability (Subramaniam & Youndt, 2005) and organizational ambidexterity (Fu et al., 2017). Instead, this study adopts EBM to represent the dynamic organizational capability needed to deploy people analytics effectively.

According to Barends, Rousseau and Briner (2014), EBM is concerned with making decisions through the conscientious, explicit, and judicious use of several sources of the best evidence available to increase the likelihood of positive outcomes and comprises of six activities including asking, acquiring, appraising, aggregating, applying, and assessing. For example, organizations must translate an issue or problem into an answerable question (asking), systematically search for and retrieve the best available evidence (acquiring), critically judge the trustworthiness and relevance of the evidence (appraising), weigh and pull together the evidence (aggregating), incorporate the evidence into the decision-making process (applying), and evaluate the outcome of the decision (assessing) (Barends et al., 2014). Likewise, EBM enables managers, professionals, and stakeholders to improve strategic decision-making based on the best available evidence (Amit & Schoemaker, 1993; Grant, 1991; Inan & Bititci, 2015; Teece et al., 1997). Accordingly, this study posits that people analytics is one of the four sources of evidence that offers managers and executives actionable insights and organizational knowledge in the form of statistical analysis, scorecards, and visualizations on various HR activities. For example, recruitment, training, performance management, and employee engagement visualizations present critical information allowing managers and senior leaders to make more informed decisions (Kapoor & Sherif, 2012; Levenson, 2018; Marler & Boudreau, 2017; McIver et al., 2018; Shrivastava et al., 2018; Ulrich & Dulebohn, 2015). Moreover, according to van der Togt and Rasmussen (2017), the individual experience, beliefs, intuition, and facts acquired through people analytics are sources of evidence HR professionals can use to enhance decision-making capabilities and better organizational results. As such, a positive relationship between people analytics and EBM is anticipated. Therefore, it is hypothesized that EBM mediates the link between people analytics and organizational performance.

Hypothesis 2: EBM mediates the relationship between people analytics and organizational performance.

5.3.3 HR Technology and People Analytics

The rapid digitalization of HR has had a significant positive impact on organizations over the past two decades (Aral et al., 2012; Ashbaugh & Miranda, 2002; Bondarouk & Brewster, 2016; Hendrickson, 2003; Johnson, Lukaszewski, & Stone, 2016; Parry & Tyson, 2011; Stone et al., 2015b). For example, HRIS allows for capturing, storing, manipulating, retrieving, and distributing HR data (Aral et al., 2012; Hendrickson, 2003; Stone et al., 2015b). Furthermore, these systems can aid in identifying and predicting short and long-term workforce trends by incorporating big data, business intelligence, and statistical applications (Garcia-Arroyo & Osca, 2019; Kapoor & Sherif, 2012; McIver et al., 2018; Mikalef, Boura, Lekakos, & Krogstie, 2019; Stone et al., 2015b; van den Heuvel & Bondarouk, 2017). More recently, advancements in HR technology platforms have led to integrating AI solutions, including chatbots, for streamlining HR processes (Black & van Esch, 2020; Buck & Morrow, 2018; van Esch & Black, 2019). In light of these advancements, this study argues that HR technology enables people analytics in several ways.

First, HRIS act as a single data source, serving as the foundation for people analytics allowing HR professionals timely access to workforce data (Johnson et al., 2016; King, 2016; Lengnick-Hall & Mortiz, 2003; McIver et al., 2018). For example, according to McIver et al. (2018), HR technology enables the collection and manipulation of various data types from several data sources that can be used to aid organizational decision-making. Similarly, HRIS enable executives, HR professionals, and line managers to gain essential insights to make strategic workforce decisions on HR issues such as performance, compensation, and talent management (Aral et al., 2012; Fernandez & Gallardo-Gallardo, 2020). Second, HR technology facilitates transforming workforce data into information through its ability to conduct statistical and predictive analysis. According to van der Togt and Rasmussen (2017), insights derived from people analytics are enabled by HR technology as they can perform sophisticated statistical analyses such as regression on longitudinal and cross-functional data. Likewise, HR technology allows HR professionals to aggregate and perform predictive analytics, which would otherwise not be possible without HR technology (Ulrich & Dulebohn, 2015). Lastly, current HR technology platforms offer a wide range of functionality, allowing HR professionals to translate data into meaningful insights through their ability to generate dashboards, scorecards, and data visualizations (Angrave et al., 2016; Marler & Boudreau, 2017; McIver et al., 2018; Ulrich & Dulebohn, 2015). According to Ulrich and Dulebohn (2015), dashboards and scorecards are descriptive analytics that HR professionals can utilize to compare and visualize various HR metrics over time. Similarly, McIver et al. (2018) suggest that dashboards offer HR professionals a way to efficiently illustrate workforce trends to help drive questions and take advantage of emerging workforce opportunities. Therefore, this study argues that HR technology will enable people analytics by acting as facilitators for transforming workforce data into organizational knowledge and insights.

Hypothesis 3: HR technology is positively associated with people analytics.

Along with the positive impact of HR technology on people analytics, this study argues that HR technology can also enhance the effect of people analytics on EBM. For instance, people analytics projects generate specific HR research questions aligned to business goals (McCartney et al., 2020; van den Heuvel & Bondarouk, 2017). This process involves gathering, organizing, and analyzing data; producing insights through various analytical approaches; and providing insights that enable managers, professionals, and other stakeholders to make evidence-based decisions (Angrave et al., 2016; McIver et al., 2018; van den Heuvel & Bondarouk, 2017).

HR technology plays a crucial role in this process, giving HR professionals the ability to gather, analyze and visualize data, enabling senior management to make more informed decisions (Kapoor & Sherif, 2012; Marler & Boudreau, 2017; McIver et al., 2018; Ulrich & Dulebohn, 2015). For example, to address the substantial variance in performance among its rigs, Maersk Drilling, uses HR technology to gather data, run analysis, and create interactive data visualizations to communicate insights to their senior management team. The insights gathered identified strong relationships among leadership quality, crew competence, safety performance, operational performance, and customer satisfaction, allowing senior management to effectively pinpoint development areas and take action (Ulrich & Dulebohn, 2015). Similarly, Johnson Controls, a multinational conglomerate headquartered in Cork, Ireland, relies on people analytics and data visualization for managerial decision-making. For example, by analyzing performance review data, the people analytics team at Johnson Controls identified that not incorporating goal setting as an element of the review was a reliable indicator and predictor of controllable turnover. As a result, senior management then altered the performance management process to focus on frequent goal setting to reduce the risk of controllable turnover (McIver et al., 2018).

As demonstrated in the cases above, HR technology offers the HR department the opportunity to visualize insights gathered from workforce data, enabling senior management to make data-driven and evidence-based decisions. Therefore, this study proposes that HR technology moderates the relationship between people analytics and EBM, such that it is stronger when HR technology is utilized at a high level rather than at a low level.

Hypothesis 4: HR technology moderates the relationship between people analytics and EBM, whereby the relationship is stronger when HR technology is utilized at a high level rather than at a low level.

5.4 Methodology

5.4.1 Data Collection

An online survey focusing on people analytics and organizational performance was developed in collaboration with a large professional recruitment agency in Ireland. The survey was pilot tested among several HR managers and senior managers with significant knowledge of the organization's performance metrics to ensure face validity. Some questions were minorly revised to achieve face validity. The survey was then distributed online to HR managers, business partners, and senior management teams in 8116 organizations. The organizations surveyed covered several sectors, including accounting, legal, banking & financial services, marketing, information and communications technology (ICT), human resources, and insurance. After the initial email invitations were distributed, 51 organizations bounced back, and 117 organizations chose to opt out of the survey, leaving 7948 as the final population. Overall, a total of 260 responses were received, generating an overall response rate of 3%. After removing incomplete responses and organizations that completed less than one-third of the survey, the valid sample size was 155, accounting for 60% of the respondents.

To examine the representativeness and detect the difference between the valid sample and the deleted responses, a one-way analysis of variance (ANOVA) was carried out. Similarly, a comparative analysis of early responses and late responses was conducted to determine the sample's representativeness (Wilcox, Bellenger, & Rigdon, 1994). This is consistent with existing studies that have checked non-response bias by comparing demographic and contextual variables between early and late respondents. (Armstrong & Overton, 1977; Fu et al., 2017; Guthrie, Flood, Liu, & MacCurtain, 2009).

The ANOVA findings showed no significant difference in organizational size, organizational age, and sectors between the complete and incomplete respondents and no significant difference among early and late respondents. Therefore, the sample was determined to be valid, and the analysis continued using the 155 respondents representing 155 organizations.

5.4.2 Sample Profile

Among the respondents, 53% were male, with 76% of respondents holding positions of HR Managers/Directors or Senior Managers. The average work tenure of respondents was nine years (SD = 8). Most organizations surveyed represented private organizations, with 88% of the respondents identifying as private. Concerning the industries represented, 30% of organizations belonged to the ICT industry, 25% were financial service firms, and 13% were professional services, including accounting, architecture, consulting and law firms. The remaining organizations represented industries, including construction, transport, and communications.

5.4.3 Measures

Organizational performance. To measure organizational performance, seven items were adopted from Delaney and Huselid (1996). Respondents were asked to rate their organization's performance relative to their competitors using a five-point Likert-type scale (1 = much weaker to 5 = much stronger). Example measures include “Ability to attract essential employees”, “Ability to retain essential employees”, “Quality of services” and “Customer service”. The reliability was assessed, showing a Cronbach's Alpha of .87.

While concerns about the use of subjective performance data can be raised, several previously published studies examining HR and organizational performance research have used self-reported performance measures (Chuang & Liao, 2010; Delaney & Huselid, 1996; Fu, Flood, Rousseau, & Morris, 2018; Sun, Aryee, & Law, 2007; Takeuchi, Lepak, Wang, & Takeuchi, 2007; Youndt, Snell, Dean, & Lepak, 1996). As the previous studies have shown, the rationale for using subjective performance data is partly due to the difficulty and inability to access the objective performance measures (Gupta, 1987; Gupta & Govindarajan, 1984, 1986). Similarly, the comparative method allows for more participants' responses rather than requiring respondents to provide exact figures (Tomaskovic-Devey, Leiter, & Thompson, 1994). Finally, as evidenced by Wall et al. (2004), subjective and objective measures of company performance are positively linked at .52.

Along with difficulty collecting objective performance, the organizations involved in this study represent several different service industries; therefore, financial performance, i.e. fee income, might not be the best indicator for firm performance. To validate the organizational performance measure, the authors conducted a second round of data collection six months later. Among the 155 organizations, only 36 responses were received. Respondents answered the same questions on organizational performance. The correlation between organizational performance at two-time points was significant (r = .36, p <.05).

EBM capability. To measure organizational EBM, six items were developed based on EBM's definition in Rousseau (2006) and Barends et al. (2014). Respondents were asked to indicate to what degree they agree or disagree with the following statements: “We translate an issue or problem into an answerable question” (asking), “We systematically search for and retrieve the best available evidence” (acquiring), “We critically judge the trustworthiness and relevance of the evidence we collect” (appraising), “We weigh and pull together the evidence” (aggregating), “We incorporate the evidence into the decision-making process” (applying) and “We evaluate the outcome of the decision” (assessing). Each item was evaluated on a five-point Likert Scale (1 = strongly disagree, and 5 = strongly agree). The Cronbach's Alpha was .93.

HR Technology. Three items were adapted from measures previously used by Aral et. al (2012). The three items developed were: “My organization has the necessary tools to conduct people analytics,” “My organization invests in the tools needed to conduct people analytics,” and “My organization has the appropriate tools for performing people analytics.” Respondents evaluated these statements based on a five-point Likert Scale (1 = strongly disagree, and 5 = strongly agree). The Cronbach's Alpha was .93.

People analytics. Given that no valid scale has been developed to measure people analytics, this study applies the theoretical framework proposed by Minbaeva (2018) and adopts questions from established scales to reflect the theoretical definition. For the first dimension, high-quality data, five questions were adopted from Pipino, Lee and Wang, (2002), which include: “The HR data we have is correct and reliable” (accuracy), “The HR data we have is sufficiently up to date” (timeliness), “The HR data we have is presented in the same format” (consistency), “The HR data we have is complete and no necessary data is missing” (completeness), and “The HR data we have is collected on a regular basis” (data process). The Cronbach's Alpha for data quality was .91.

For the second dimension, analytical competency, five items were adopted from Kryscynski et al. (2018). Example items include: “Our HR Department translates data into useful insights”, “Our HR department identifies problems that can be solved with data” and “Our HR Department effectively uses people analytics to create value for my organization”. The Cronbach's Alpha for analytical capability was .95. Finally, the strategic ability to act was operationalized through three questions adopted from Minbaeva (2018), including “Our HR Department has success stories to justify people analytics projects”, “Our HR Department inspires relevant organizational stakeholders (e.g., senior management teams and line managers) to take action on the basis of their findings” and “The data-driven insights that we provide are used by our organization's stakeholders”, The Cronbach's Alpha for analytical capability was .86.

Each of the three dimensions of the people analytics measure was evaluated based on a five-point Likert Scale (1 = strongly disagree, and 5 = strongly agree). A second-order CFA was conducted for the people analytics measure to examine the new scale's validity. The model fit indexes indicated an acceptable model fit for the second-order CFA with three first-order dimensions (χ^2/df = 171.65/72 = 2.38, p < .001; CFI = .95; TLI = .93; RMSEA = .09; SRMR = .05). Considering people analytics as a theorized higher-order concept in this study, as well as the CFA's support for the higher-order factor structure, people analytics was treated as one overall concept with three dimensions in the model test.

Control Variables. In the analysis, several contextual variables with the potential to influence the use of people analytics were controlled for including, EBM, HR technology, and organizational performance. Likewise, organization size, organization age, organization type (multinational or domestic), sector and industries were also controlled for. Organization size was measured using three categories: 1 = small organizations (less than 50 employees), 2 = medium organizations (between 50 and 250 employees) and 3 = large organizations (more than 250 employees). Organization age was operationalized as the natural log of the actual organization age. Organization type (multinational or domestic) was measured using a dummy variable (1 = multinational companies; 0 = domestic companies). Sector was measured using a dummy variable (1 = private, 0 = public or semi-state). The industry was measured by four categories (1 = professional services including accounting, advertising, architecture, consulting and law firms; 2 = ICT; 3 = financial services including banking, insurance, compliance and risk firms; and 4 = other services including education, healthcare, pharmaceutical etc.). Three dummy variables were created for the industry variable using ICT as the baseline category.

5.4.4 Common Method Bias

It was necessary to check whether common method bias was present in the study since all variables were collected from a single source. To address this concern, this study follows several recommendations made by Podsakoff, MacKenzie, Lee, and Podsakoff (2003) and Podsakoff, MacKenzie, and Podsakoff (2012). For instance, before launching the survey, it was piloted with a group of HR managers and was revised and retested several times. Changes made as a result included the wording and order of the questions. Likewise, during the data analysis stage, the common method variance was assessed by carrying out a series of CFA to establish the validity of the studied variables. Likewise, one unrelated common factor was added to the CFA with enforced equal factor loadings to all items in evaluating the common method bias

Table 5.1 Descriptive Statistics and Correlations of Study Variables

Variables	Mean	SD	1	2	3	4	5	6	7	8
1. Organizational performance	3.57	.62								
2. EBM	3.68	.68	.44**							
3. Technology	3.08	.90	.20*	.22**						
4. People analytics	3.43	.72	.35**	.37**	.66**					
5. Organization size	1.95	.79	.01	-.07	.21*	.07				
6. Organization age	3.10	.99	-.11	-.23**	.06	-.03	.44**			
7. Sector	.89	.32	.05	.00	-.14	-.01	-.17*	-.14		
8. Organization type	.56	.50	-.14	-.05	.04	-.07	.06	-.09	-.03	
9. Industry	2.78	1.04	-.11	-.03	-.06	-.08	.09	.09	-.05	.06

Note: N= 134 (listwise) ** *p* <.01 **p* <.05

Table 5.2 Fit Statistics from Measurement Model Comparison

Models	χ^2/df	*CFI*	*TLI*	*RMSEA*	*SRMR*	$\Delta\chi^2$	Δdf
Full measurement model	**236.93/143**	**.95**	**.94**	**.07**	**.07**		
Model A[a]	498.61/146	.82	.78	.13	.13	261.68***	3
Model B[b]	371.73/146	.88	.86	.10	.09	134.80***	3
Model C[c]	842.54/148	.64	.58	.18	.16	605.61***	5
Model D[d]	412.52/146	.86	.84	.11	.12	175.59***	3
Model E[e]	459.60/146	.84	.81	.12	.15	222.67***	3
Model F[f]	669.10/148	.73	.68	.15	.16	432.17***	5
Model G[g] (Harman's Single Factor Test)	1010.77/149	.55	.48	.19	.18	773.84***	6

Notes: N = 153, ****p* <.001; χ^2=chi-square discrepancy, df=degrees of freedom; CFI=Comparative Fit Index; TLI= Tucker-Lewis Index; RMSEA=Root Mean Square Error of Approximation; SRMR= Standardized Root Mean Square Residual; =difference in chi-square, =difference in degrees of freedom. In all measurement models, error terms were free to covary to improve fit and help reduce bias in the estimated parameter values. All models are compared to the full measurement model
.

[a] = People analytics and evidence-based management combined into a single factor.

[b] = People analytics and technology combined into a single factor.

[c] = People analytics, evidence-based management and technology combined into one factor.

[d] = Evidence-based management and organizational performance combined into a single factor.

[e] = People analytics and organizational performance combined into a single factor.

[f] = People analytics, evidence-based management and organizational performance combined into a single factor.

[g]=All factors combined into a single factor.

(Podsakoff et al., 2012). The squared regression estimates indicated a common variance of 3 percent, indicating no significant concern for common method bias.

5.5 Results

Table 5.1 presents the descriptive statistics of the core variables in this study, including the mean, standard deviation, and correlations.

5.5.1 Measurement Models

Analysis was conducted using Mplus 8.0. A full measurement model was tested using three pre-calculated variables (data quality, analytical capability, and strategic ability to act) loaded on one general factor representing people analytics. EBM, HR technology, and organizational performance items loaded on to their respective factors. According to the cut-off criteria for fit indexes (Hu & Bentler, 1999), the four-factor model showed a good model fit (χ^2/df = 236.93/143 = 1.66, $p < .001$; CFI = .95; CLI = .94; RMSEA = .07; SRMR = .07) with factor loadings higher than .55 ($p < .001$), a X^2/df values less than 3, a CFI value greater than or equal to .95, RMSEA less than .08, and an SRMR of less than .08.

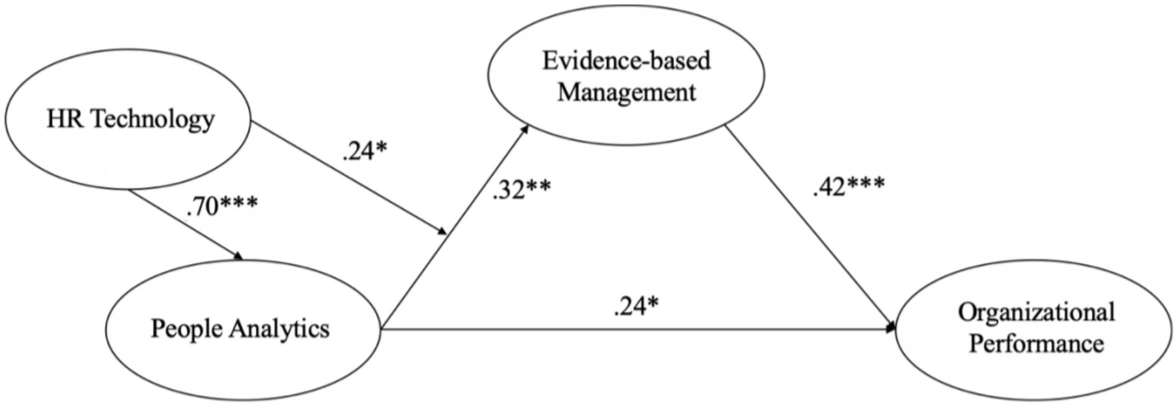
Seven χ^2 difference tests were carried out to compare the full measurement model to alternative nested models, as shown in Table 5.2. The comparison results reveal that the model fit of the full measurement model was significantly better than the alternative models (all at p <.001), suggesting that the study's variables are distinct.

5.5.2 Structural Models

Moderation structural equation modelling was conducted in Mplus 8.0. Figure 5.1 presents the results.

Hypothesis 1 proposed that people analytics would be positively linked to organizational performance. Results in Figure 5.1 show that the standardized coefficient of people analytics on organizational performance was positive and significant (β = .24, $p < .05$). Therefore, Hypothesis 1 was supported.

Figure 5.1 Moderation SEM Results



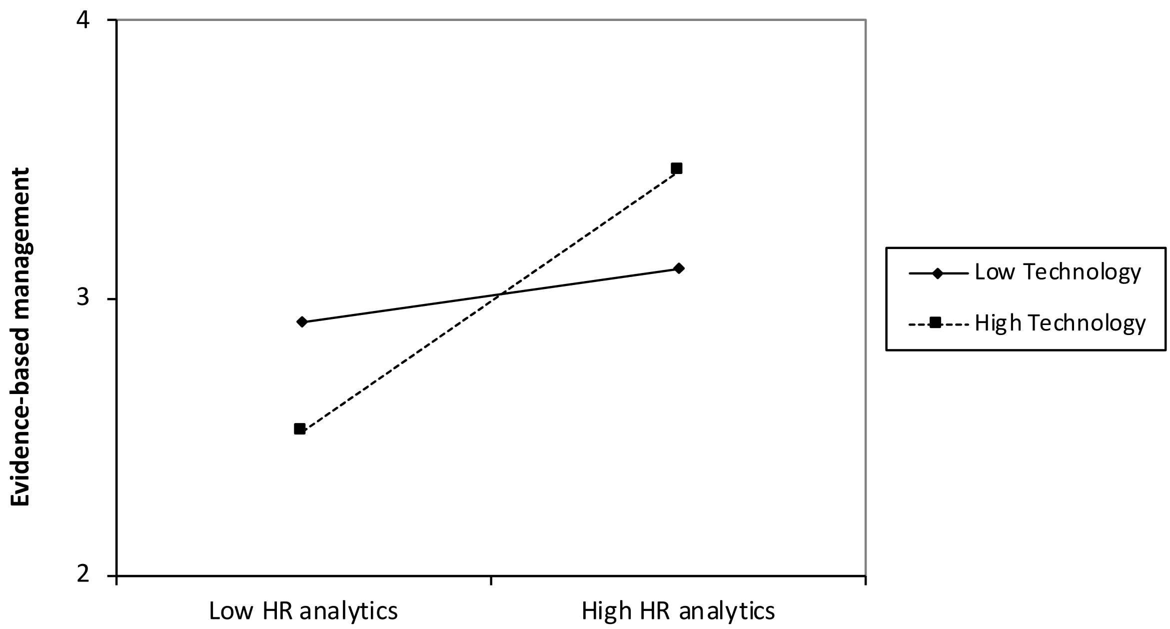
	People Analytics	Evidence-based Management	Organizational Performance
Firm size	-.00	-.03	.01
Firm age	-.01	-.20*	-.01
Organization type	-.07	-.05	.22**
Sector	-.01	-.03	.07
Industry dummy 1	.02	.03	-.23**
Industry dummy 2	.05	.01	-.24**
Industry dummy 3	.01	.10	-.08

Note: N= 134 (listwise) ** *p* <.01 **p* <.05

Hypothesis 2 proposed that EBM would mediate the relationship between people analytics and organizational performance. Figure 5.1 shows that the standardized people analytics coefficient on EBM was (β = .32, p < .01). Furthermore, EBM's standardized coefficient on organizational performance was positive and significant (β = .42, p < .001), meeting the two criteria for mediation. To further test EBM's mediating effect in the relationship between people analytics and organizational performance, this study adopted a bootstrapping test recommended by Hayes and Preacher (2014). The bootstrapping test results reveal that the indirect effect of people analytics and organizational performance through EBM was .17 (p < .05), with a 95% confidence interval between .02 and .32. As such, hypothesis 2 was supported, suggesting that EBM mediates the relationship between people analytics and organizational performance.

Hypothesis 3 proposed that HR technology is positively associated with people analytics. It is supported by the positive and significant coefficient for HR technology on people analytics (β = .70, p < .001). Hypothesis 4 proposed that technology would moderate the relationship between people analytics and EBM such that the link is stronger under a high level of technology. The moderated SEM results in Figure 5.1 indicate that people analytics and HR technology's interaction term was significantly associated with EBM (β = .24, p < .01). Similarly, the interaction between people analytics and HR technology on EBM was plotted and is shown in Figure 5.2.

Figure 5.2 Interaction Plot of People Analytics and HR Technology on EBM



As shown in Figure 5.2, under a high HR technology level, the slope for people analytics on EBM was stronger than the slope with a lower level of HR technology. Therefore, Hypothesis 4 on HR technology's moderating role in the relationship between people analytics and EBM was supported.

5.6 Discussion

Despite the claimed importance of people analytics, evidence supporting the performance impact of people analytics on organizational performance remains underdeveloped (Baesens et al., 2017; Greasley & Thomas, 2020; Huselid, 2018; Levenson & Fink, 2017; Marler & Boudreau, 2017; Rasmussen & Ulrich, 2015). As such, this study set out the first attempt to (1) theorize and establish the relationship between people analytics and organizational performance; and (2) understand the process and conditions under which people analytics can influence organizational performance. Drawing upon the resource-based view of the firm (Barney, 1991), dynamic capabilities (Teece et al., 1997), and EBM (Barends et al., 2014; Rousseau, 2006; Rousseau & Barends, 2011), this study theorized an integrated model linking HR technology, people analytics, EBM, and organizational performance. Using a sample of 155 organizations based in Ireland, the moderation structural equation modelling results provided full support for the theoretical model. The findings suggest that when people analytics is linked with EBM practices, one outcome of this relationship is a higher level of organizational performance. Furthermore, the results provide empirical support for the claim that HR technology enables people analytics and moderates the relationship between people analytics and EBM.

5.6.1 Theoretical Contributions

The findings of this study make several contributions to the fields of people analytics and EBM. First, this study offers a very timely investigation of whether people analytics impacts organizational performance. Due to the growing interest in people analytics, organizations have begun to buy-in to people analytics by assembling people analytics teams dedicated to using workforce data to make strategic workforce decisions (Andersen, 2017; McIver et al., 2018; Rasmussen & Ulrich, 2015). However, very little empirical evidence supports the impact people analytics has on organizational performance (Marler & Boudreau, 2017; McIver et al., 2018; Rasmussen & Ulrich, 2015; van der Togt & Rasmussen, 2017). According to McIver et al. (2018), despite the great enthusiasm for adopting people analytics in practice, there remains a misunderstanding of how organizations can leverage and use people analytics to increase organizational performance. Furthermore, King (2016) argues that although the practice of conducting people analytics has risen in popularity, organizations should only begin to invest in people analytics programs if they can demonstrate value and increase organizational performance. This research has responded to the above calls by seeking support for the positive effect of people analytics on organizational performance and offers evidence of the performance impact of people analytics.

Secondly, this study promotes current people analytics research by providing evidence suggesting a relationship between HR technology and people analytics. In recent years, scholars have theorized that HR technology is critical in enabling the people analytics process. For example, Marler and Boudreau (2017) and McIver et al. (2018) have suggested that people analytics are enabled by HR technology as it allows for the collection, manipulation, and reporting of structured and unstructured workforce data. Furthermore, several scholars have also begun to suggest that people analytics are enabled by HR technology as they allow HR professionals to perform complex statistical analysis, leading to the development of predictive analytics and sophisticated people models (Levenson, 2005; Sharma & Sharma, 2017; Ulrich & Dulebohn, 2015; van der Togt & Rasmussen, 2017). Despite these claims, evidence supporting the enabling role of HR technology in people analytics has yet to be discussed in the extant people analytics literature. Therefore, this paper supports these claims, indicating a link between HR technology and people analytics, where HR technology is a critical component in enabling people analytics.

Thirdly, this study contributes to people analytics research by exploring the process, (i.e. the mediating role of EBM) through which people analytics influences organizational performance. As reviewed earlier, the research examining the performance impact of people analytics is scarce within the extant literature. Likewise, evidence illustrating the process of how people analytics can influence organizational performance is non-existent, making the analysis of intervening variables essential both theoretically and empirically. This is only the first step in identifying the underlying linkage between people analytics and organizational performance; however, this study undoubtedly contributes to this endeavour. Furthermore, this study found support for the moderating role of HR technology, indicating that when a higher level of HR technology is utilized, the data, information, and insights generated via people analytics can be transformed into evidence-based decisions. In other words, the relationship between people analytics and EBM is strengthened by the existence and utilization of HR technology. Similarly, this finding improves our understanding of people analytics' impact on EBM by recognizing EBM's mediating role in the relationship between people analytics and organizational performance. Furthermore, the study sheds light on how HR technology can act as an enabler for people analytics and a moderator between people analytics and EBM. Therefore, it offers a unique contribution to people analytics research, offering evidence supporting *how* and *when* people analytics can increase organizational performance.

Lastly, this study contributes toward EBM research significantly by identifying an antecedent of EBM (i.e., people analytics), as well as offering evidence supporting the performance impact of EBM. To date, EBM research has seen increasing attention in both research and practice. However, there has been limited attention paid to directly address EBM's performance impact, which is "of the utmost importance" (Reay, Berta, & Kohn, 2009, p. 13). Moreover, the organizational level factors which drive EBM remain unknown. Thus, this paper contributes to EBM research by offering a critical organizational factor (people analytics) that promotes the adoption of EBM practices within organizations.

5.6.2 Implications for Practice

The findings offer several implications for practitioners. First, this study provides evidence for the positive impact of people analytics on organizational performance, suggesting that investing in people analytics and employing EBM practices can increase organizational performance. Second, the study provides supporting evidence for the critical role that HR technology plays in enhancing the impact of people analytics on EBM. In other words, this study proposes that high investment in HR technology has a more significant impact on people analytics and EBM. Thus, it is critical for HR managers and business partners to have the necessary tools to effectively transform and translate high-quality workforce data into organizational insights.

In addition, this study is significant for organizations looking to improve their current HR technology capabilities or are starting to implement or expand their current people analytics activities. The study finds that HR technology offers HR managers and business partners the ability to run reports, create dashboards, visualizations, monitor KPI's, and perform predictive analytics. Thus, providing several sources of additional information enabling evidence-based decision- making.

Lastly, this study suggests that establishing and cultivating a culture focused on using EBM and evidence-based decision-making has significant advantages for improving organizational performance. Likewise, support is found for the important role of people analytics in enabling organizations to adopt EBM practices. For instance, people analytics offers information through mediums such as dashboards, scorecards, and predictive analytics. According to Rousseau and Barends (2011), these sources of organizational knowledge create a link between people analytics and EBM, allowing HR managers and business partners to make more informed decisions about their workforce. Therefore, organizations should foster a culture of EBM and incorporate EBM into their decision-making process facilitated by people analytics.

5.6.3 Limitations and Future Research

Despite the significant implications for theory and practice in people analytics, several limitations are evident in this study. Firstly, this study adopted a cross-sectional design, which does not allow us to test the causality between the studied variables. Second, the small sample size and context where it was conducted is a limitation of the study. Future research is encouraged to collect longitudinal data among multi-industry, multi-country, and large databases to test for the causality between the key variables in this study and the generalizability of the findings in this study. The results on the significant correlation coefficient between HR technology on people analytics ($r = .66$, $p < .01$) as well as the path coefficient of HR technology on people analytics ($\beta = .70$, $p < .001$) raise concerns for the validity of the measurements. Accordingly, future research should adapt cross-disciplinary measures from the big data, marketing, or information technology literature to better test this relationship. Furthermore, future research is warranted to further investigate the connection between HR technology and people analytics. For instance, should HR technology be incorporated as a fourth component of people analytics? Or does it only act as an enabler in the people analytics process?

As illustrated, organizations utilize various levels of HR technology to perform people analytics. At the most basic level, organizations rely on HRIS and Excel reporting capabilities. In contrast, more advanced organizations will also utilize these platforms but will integrate them with more advanced forms of HR technology (e.g. BI tools, AI-enabled platforms). This raises the question of whether the use of more advanced HR technology leads to more insightful people analytics? And if so, how significant are these insights compared to those derived from basic level technology? Equally important is the notion that organizations currently engaging with people analytics often rely on people analytics teams to conduct the analytics (i.e. transforming and translating high-quality workforce data into organizational insights), rather than an individual employee (Andersen, 2017; McCartney et al., 2020; McIver et al., 2018; Peeters et al., 2020). However, very little attention has been paid to exploring the composition of people analytics teams or their impact on HR practices and organizational performance (McCartney et al., 2020). For instance, given the complex range of skills required to effectively transform and translate high-quality workforce data into organizational insights, people analytics teams need members to have various complimentary KSAO's (Andersen, 2017; McCartney et al., 2020; McIver et al., 2018). As such, it is essential that research examining the complimentary KSAO's and synergies among specific team members that enable the emergence of highly effective people analytics teams be explored. Likewise, a significant way to move people analytics research forward would be to explore how people analytics teams can help develop or enhance HR practices and their effect on organizational performance.

5.7 Conclusion

While people analytics is gaining increasing interest as a field of study, people analytics is still a relatively new concept. As a result, scholars and practitioners are poised to conduct research highlighting how HR's digitalization and the growing amount of people data can impact HR decision-making and organizational outcomes. The present study sheds light on the people analytics research by identifying the direct, indirect and conditional impact of people analytics on organizational performance. By doing so, this study offers the first step toward understanding and uncovering the performance impact of people analytics.

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CHAPTER – 6 DISCUSSION

6.1 Introduction

Although research in people analytics has dramatically increased over the past decade, several questions remain unanswered. As such, this dissertation set out to offer insight into three research gaps in people analytics centred on three research questions. They included the (1) lack of systematic investigation of the debates and challenges faced by people analytics; (2) unestablished KSAOs required to influence people analytics; and (3) unknown performance impact of people analytics.

To address the above research gaps, the dissertation adopted a three-study approach, with each study having its own research aims and objectives that link to the overarching research question. Study 1 "*Promise Vs Reality: Ongoing Debates in People Analytics*" was a systematic literature review focused on answering the research question of what debates and challenges are emerging as a result of people analytics adoption. The review illustrated several emerging debates, including inconsistency among the concept and definition of people analytics, people analytics ownership, ethical and privacy concerns of using people analytics, missing evidence of people analytics impact, and readiness to perform people analytics.

Using Study 1 as a foundation, Study 2 "*Complementarity Human Capital: Linking Analytical and Storytelling Skills to People Analytics Performance*" focused on addressing the research question of what factors contribute to the success of people analytics. Study 2 found that storytelling skills are positively associated with task and team performance. Moreover, the complementarity effect of analytical and storytelling skills suggested that when the two human capital inputs were combined, they positively influenced task and team performance.

Extending Study 1 and Study 2, Study 3 "*Bridging the Gap: Why, How, and When People Analytics Can Impact Organizational Performance*" aimed to address how people analytics impacts organizational performance. Study 3 found that people analytics positively impacts organizational performance at the organizational level through EBM. Further, the results indicated that HR technology enables people analytics and strengthens the impact of people analytics on EBM. Overall, the three studies add to our understanding of the rapidly evolving field of people analytics and provide significant original contributions.

The remaining sections of this chapter present a broad summary of the theoretical contributions made by the dissertation in the areas of people analytics, human capital resources, human capital complementarities, and EBM. Next, practical implications are discussed, offering insight targeted towards practitioners surrounding the impact of people analytics on organizational performance, HR technology, and the human capital inputs critical to people analytics success. Finally, the chapter concludes by discussing the limitations of the dissertation while presenting several areas for future research.

6.2 Theoretical Contributions

The findings of this dissertation make several contributions to the strategic HRM and people analytics literature. First, this research extends our understanding of people analytics. The digitalization of HR led by recent advances in information technology and the desire to make evidence-based decisions, people analytics has seen increased adoption amongst organizations (Dahlbom, Siikanen, Sajasalo, & Jarvenpää, 2019; Fernandez & Gallardo-Gallardo, 2020; Marler & Boudreau, 2017; van den Heuvel & Bondarouk, 2017). Consequently, this has spurred academic research focused on applying people analytics (Harris et al., 2011; Kane, 2015; McIver et al., 2018; Peeters et al., 2020; Simón & Ferreiro, 2018) and the conceptualization of people analytics (Falletta & Combs, 2020; Fernandez & Gallardo-Gallardo, 2020; Margherita, 2020). However, despite the significant increase in academic research, many questions concerning people analytics and its effect remain unresolved, prompting additional scholarly attention (Huselid, 2018). Specifically, it remains unknown what debates and challenges are arising as a result of people analytics adoption, what factors contribute to people analytics, and how does people analytics impact organizational performance. This dissertation answers these questions and extends our understanding of people analytics by systematically examining the current literature on people analytics (Study 1); by empirically investigating the required KSAOs contributing to people analytics performance (Study 2); and finally, by examining the indirect performance impact of people analytics via EBM and HR technology (Study 3).

In particular, Study 1 found that five distinct themes are emerging within the people analytics literature, including the inconsistency among the concept and definition of people analytics, people analytics ownership, ethical and privacy concerns of using people analytics, missing evidence of people analytics impact, and readiness to perform people analytics. Study 2 found that analytical skills were only significant in improving team performance rather than the individual people analytics task performance. However, storytelling skills were significant and positively associated with both individual people analytics task performance and team performance. Additionally, Study 2 found that when analytical and storytelling skills are combined, they produce higher people analytics performance. Study 3 found support that people analytics positively impacts organizational performance by developing the organization's EBM capability, moderated by HR technology.

Collectively, findings from the three studies are consistent with prior work in people analytics. For example, the systematic review shares themes touched upon by Fernandez and Gallardo-Gallardo (2020), Margherita (2020), and Marler and Boudreau (2017), validating the inconsistency among the concept and definition of people analytics and missing evidence of people analytics impact. Moreover, the theme of ethical and privacy concerns of using people analytics has been discussed by Jeske and Calvard (2020) and Tursunbayeva, Pagliari, Di Lauro, and Antonelli (2021) as a growing concern due to big data in HRM. The research findings are also consistent with previous claims made by scholars concerning the importance of storytelling skills (Andersen, 2017; Falletta & Combs, 2020; McCartney et al., 2020; McIver et al., 2018; Minbaeva, 2018). For instance, Minbaeva (2018) proposed that people analytics professionals must convey insights to data consumers in HR and business language. Likewise, McCartney et al. (2020) suggested that HR Analysts require the ability to interpret and frame insights extracted from workforce data into a compelling narrative. This dissertation also finds commonalities concerning the influence of HR technology on people analytics. For instance, scholars have theorized that HR technology is critical in enabling the people analytics process as it allows for the collection, manipulation, and reporting of structured and unstructured workforce data (Marler & Boudreau, 2017; McIver et al., 2018). This dissertation supports these claims, indicating a link between HR technology and people analytics, where HR technology is a critical component in enabling people analytics.

In addition to drawing parallels from existing people analytics research, the dissertation offers new and original contributions to the field of people analytics. For instance, Study 1 outlined several debates and challenges quickly evolving within the existing people analytics literature. For example, scholars have begun to question whether HR should retain ownership of people analytics or whether it is more appropriate for the function to be relocated outside HR. Furthermore, the study situates two new debates within the people analytics literature surrounding whether people analytics has a role to play in empowering employees and organizations in times of crisis and how people analytics can impact the growing need for sustainability and green HRM practices. Additionally, although scholars have identified various KSAOs as critical to the success of people analytics, researchers have yet to adequately resolve this gap by empirically examining the significance of specific KSAOs and linking them to people analytics results. Study 2 offers original insight into the KSAOs that contribute to people analytics success by examining the direct effect of analytical and storytelling skills on individual and team people analytics performance. Moreover, the findings suggest that the synergistic relationship between analytical skills and storytelling skills directly improves individual task performance. The third study offers a very timely investigation of whether people analytics impacts organizational performance. To date, very little empirical evidence has supported the notion that people analytics can impact organizational performance (Marler & Boudreau, 2017; McIver et al., 2018; Rasmussen & Ulrich, 2015; van der Togt & Rasmussen, 2017). For example, despite the enthusiasm for implementing people analytics in practice, there is still a misunderstanding of how organizations may leverage and apply people analytics to improve organizational performance (McIver et al., 2018). This dissertation has addressed this gap by seeking support for the positive effect of people analytics on organizational performance and offering evidence of the performance impact of people analytics through RBV and EBM.

The second major contribution of this research is to human capital resources and the human capital complementarities literature. Furthermore, primarily in Study 2, the dissertation provides empirical support for the effects of human capital and human capital complementarities on performance. The focus of human capital resources to date has been concerned with exploring how one human capital resource can affect performance, with little attention paid to demonstrating how different human capital inputs interact to create super-additive value (Nyberg et al., 2018; Ployhart & Cragun, 2017; Ployhart et al., 2014). In addition, scholars have only recently begun to examine the effect of complementarity human capital, using professional sports as an example. However, these studies are few and far between. As such, this dissertation adds much-needed empirical evidence offering insight into how complementarity relationships between individual KSAOs lead to higher levels of performance within the context of people analytics.

Finally, this study adds to our understanding of how people analytics affects performance. It accomplishes this primarily in Study 3 by combining strategic human capital theory (Becker, 1964), RBV (Barney, 1991), and EBM (Rousseau & Barends, 2011). The notion that people analytics will positively impact organizational performance underscores the current state of people analytics in practice. However, despite several case studies claiming the impact of people analytics, research demonstrating the success of people analytics remains rare, with organizations offering little evidence in supporting that people analytics can help strategic decision making (Baesens et al., 2017; Greasley & Thomas, 2020; Huselid, 2018; Levenson & Fink, 2017; Marler & Boudreau, 2017; Rasmussen & Ulrich, 2015). Study 3 explores the process (i.e., the mediating role of EBM) through which people analytics influences organizational performance. In addition, Study 3 finds support for the moderating role of HR technology, indicating that when a higher level of HR technology is utilized, the data, information, and insights generated via people analytics can be transformed into evidence-based decisions. Therefore, the dissertation offers a unique contribution to people analytics by providing evidence supporting *how* and *when* people analytics can increase organizational performance. In addition, Study 2 found the importance of analytical and storytelling skills to drive people analytics performance. Overall, the dissertation finds strong support for the performance impact of people analytics, using different methods and at varying levels of analysis. Doing so builds theoretical foundations for the performance impact of people analytics.

6.3 Practical Implications

The findings of the dissertation also offer implications for practitioners. First, at the organizational level, Study 3 provides evidence for the positive impact of people analytics on organizational performance, suggesting that investing in people analytics coupled with EBM practices can increase organizational performance. Furthermore, this study indicates that establishing and cultivating a culture focused on using EBM and evidence-based decision-making has significant advantages for improving organizational performance. Likewise, support is found for people analytics' role in enabling organizations to adopt EBM practices. For instance, people analytics offers information through mediums such as dashboards, scorecards, and predictive analytics. According to Rousseau and Barends (2011), these sources of organizational knowledge create a link between people analytics and EBM, allowing HR managers and business partners to make more informed decisions about their workforce. Thus, organizations should foster a culture of data-driven decision-making by incorporating EBM practices and people analytics. Study 3 also provides supporting evidence highlighting that high investment in HR technology has a more significant impact on people analytics and EBM. Thus, it is critical for HR managers and business partners to have the necessary tools to transform and translate high-quality workforce data into organizational insights effectively. This finding has significant implications for organizations looking to improve their current HR technology capabilities or are starting to implement or expand their current people analytics activities.

The findings also offer insight at the individual level. The results from Study 2 suggest that both analytical and storytelling skills are important in performing people analytics. For example, from an analytics perspective, HR Analysts need to have the skills to produce key metrics and run statistical models using various software packages (e.g., Excel, SPSS, PowerBI, R, Stata, or Tableau). In contrast, HR Analysts require storytelling skills which represents the ability to effectively communicate and visualize the impact of data on business performance to influence decision-making. Furthermore, the findings suggest that a complementarity relationship exists between analytical and storytelling skills where, when combined, they offer superior performance. As such, HR departments should concentrate on building their people analytics resource around HR Analysts who have high levels of analytical and storytelling skills so that they can analyze, interpret, and translate insights into a compelling data story.

Thirdly, the findings offer valuable insight to HR departments looking to begin or have just started their people analytics journey. For instance, storytelling skills were positively associated with individual people analytics task and team performance, while analytical skills were only significant concerning team performance. This means that if HR departments want to invest in people analytics or are just getting started, it is essential to build storytelling capabilities first, as this will provide the most benefit in the short term. Subsequently, HR departments can develop their analytical skills to take advantage of the complementarity relationship between analytical and storytelling skills. In other words, when developing people analytics capabilities, hire storytelling skills and train for analytical skills.

Lastly, from a broad standpoint, Study 1 suggests that to move the field of people analytics forward, it is imperative that academic researchers and HR practitioners form mutually beneficial partnerships where challenges faced by HR professionals inform academic research. By facilitating discourse between researchers and people analytics stakeholders, together, each party can inform the other, leading to the development of relevant knowledge through the generation of specific research questions, building theories, and translating insights into practical solutions.

6.4 Limitations and Future Research

Despite the significant implications for theory and practice in people analytics, several limitations are evident in the dissertation. First, studies 2 and 3 adopted a cross-sectional design, not allowing to test for causality between the studied variables. They are also limited in small sample sizes and responses concentrated in North America and Europe. Future research is encouraged to collect longitudinal data sets from a larger sample specifically in geographical areas underrepresented in the dissertation, such as Asia, South America, Africa, and Australia/Oceania, to test for the causality between the key variables and generalizability of the findings in this research.

Second, specific to Study 2, given time constraints and generally small team sizes, it was difficult to obtain multiple team member responses. As such, an individual self-report was used to represent the people analytics team performance variable. To address this limitation of the research design, future research should concentrate on gathering responses from larger people analytics teams and obtain multiple team member responses and aggregate them increasing the reliability and validity of the people analytics team performance construct.

Third, specific to Study 3, the findings on the significant correlation coefficient between HR technology on people analytics (r = .66, p < .01) as well as the path coefficient of HR technology on people analytics (β = .70, p < .001) raise concerns for the validity of the measurements. Accordingly, future research should adapt cross-disciplinary measures from the big data, marketing, or information technology literature to better test this relationship.

In addition to future research addressing the limitations included in the dissertation, each of the three studies has also outlined several other areas of future research that will aid in advancing the field of people analytics. These areas for future research are summarized in Table 6.1.

6.5 Summary

This chapter presented a broad summary of the dissertation's theoretical contributions in the areas of HRM and people analytics. Next, practical implications were discussed, offering insight targeted towards practitioners surrounding the impact of people analytics on organizational performance, HR technology, and the human capital inputs critical to people analytics success. Finally, the chapter concluded by discussing the limitations of the dissertation while presenting several areas for future research.

Table 6.1 Areas for Future Research

Study	Areas of Future Research
Study 1 - Promise Vs. Reality: Ongoing Debates in People Analytics	• How can researchers bridge the academic-practitioner gap in people analytics? • Which existing theories can offer insight into evaluating people analytics success? • What ethical and privacy concerns arise as a result of people analytics? • Does ownership of people analytics matter? • Can people analytics employer employees and organizations in times of crisis? • Can people analytics impact the growing need for sustainability and facilitate the adoption of green HRM practices?
Study 2 - Complementarity Human Capital: Linking Analytical and Storytelling Skills to People Analytics Performance	• To what degree will analytical skills be relevant for employees in people analytics roles if this will be the primary responsibility of AI moving forward? • How can human capital complement the new form of digital capital? • Investigate the link between unit-level human capital resources and organizational outcomes through people analytics • How can unit-level human capital resources combine and lead to sustainable competitive advantage • Investigate whether people analytics is a causal complementarity that can develop and acquire additional human capital resources.
Study 3 - Bridging the Gap: Why, How, and When People Analytics Can Impact Organizational Performance	• Is technology a fourth component of people analytics or simply an enabler? • Does the use of more advanced HR technology lead to more insightful people analytics? And if so, how significant are these insights compared to those derived from basic level technology? • Exploring the composition of people analytics teams and their impact on HR practices and organizational performance.

Chapter – 7 Conclusion

People analytics has been considered a game changer for the future of HRM (van der Togt & Rasmussen, 2017). However, despite its promise to revolutionize the HRM function, the current reality of people analytics is more skeptical than optimistic, generating more questions than answers. As such, this dissertation aimed to address three main research gaps, i.e., the lack of systematic investigation of the challenges and debates in people analytics, the unknown or inconsistent findings on the required skills for people analytics, and the unknown performance impact of people analytics. Drawing on the RBV, EBM, and strategic human capital theory, this dissertation makes an original contribution to knowledge by answering the following research questions: (1) What debates and challenges are emerging as a result of people analytics adoption? (2) What factors contribute to the success of people analytics? (3) How does people analytics impact organizational performance? To do so, the dissertation was organized into three papers, each with its own set of research aims and objectives that logically interconnect to the research questions.

In particular, Study 1 presented a systematic literature review addressing the debates and challenges emerging as a result of people analytics adoption. Study 2 built on the findings from Study 1 by investigating the impact of analytical and storytelling skills and their complementarity effect on people analytics performance. Doing so offered insight into the second research question of what factors contribute to people analytics performance, finding that the human capital inputs of analytical and storytelling skills individually and together contributed to individual and team people analytics performance. Finally, Study 3 addressed the performance impact of people analytics on organization performance while also identifying two factors (i.e., EBM and HR technology) that contributed to the success of people analytics at the organizational level.

Overall, despite its limitations, the dissertation makes significant contributions to people analytics and strategic human capital. First, the dissertation illustrates several emerging debates and challenges faced by people analytics, including inconsistency among the concept and definition of people analytics, people analytics ownership, ethical and privacy concerns of using people analytics, missing evidence of people analytics impact, and readiness to perform people analytics. As a result, an updated research agenda is proposed that focuses on developing a strong collaboration between academic researchers and HR practitioners. Second, the dissertation finds that analytical and storytelling skills are essential in performing people analytics and that when combined, they offer superior performance due to their complementarity relationship. This finding provides new and original knowledge to people analytics concerning what factors contribute to people analytics success while also contributing to strategic human capital by finding evidence supporting individual KSAOs can complement each other leading to higher performance outcomes. Finally, evidence is found for the positive impact of people analytics on organizational performance. Moreover, it is found that when HR departments have the right HR technology in place and embrace EBM practices, these two factors contribute to higher levels of organizational performance.

Although considerable progress has been made in the emerging area of people analytics, it is evident that the field has much to overcome. Overall, this dissertation offers the first step toward understanding and uncovering the performance impact of people analytics and serves as a starting point to unlock the puzzle of how human capital can influence people analytics performance.

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