BRIDGING DIFFERENT WORLDS:

Using people analytics effectively for improving well-being and performance

Tina Peeters

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Introduction

Introduction

Sparked by an ever-increasing amount of data, organizations progressively find ways to use them to their competitive advantage (Davenport & Harris, 2017). Some tech giants have made them their core business (e.g. Meta, Amazon, Uber). In contrast, others have used them within specific business domains such as finance, marketing, and information systems to increase their business outcomes (Holsapple, Lee-Post, & Pakath, 2014). Recently, organizations have begun to use the data of their workforce too (Cascio, Boudreau, & Fink, 2019; Levenson, 2005). This practice is called people analytics and refers to "the analysis of employee and workforce data to reveal insights and provide recommendations to improve business outcomes" (Ferrar & Green, 2021). People analytics can support any employee-related decision (Ellmer & Reichel, 2021; Huselid & Minbaeva, 2019), help the Human Resources (HR) function become more strategic (Angrave, Charlwood, Kirkpatrick, Lawrence, & Stuart, 2016), and allow an organization to prepare for the future (Guenole, Ferrar, & Feinzig, 2017). Practically, people analytics can, for example, identify internal and external talents, create succession pipelines, predict which talents may be tempted to leave the organization and provide recommendations on how they may be retained most efficiently (Minbaeva & Vardi, 2019; Rosenbaum, 2019; Yuan, Kroon, & Kramer, 2021). Due to these proposed benefits, organizations invest heavily in people analytics (Ledet, McNulty, Morales, & Shandell, 2020).

Despite that people analytics is top of mind for 70% of companies' executives, most organizations struggle to use it effectively (Ledet et al., 2020). Orgvue (2019), for example, investigated the use of people analytics among 400 HR professionals of large companies (< 1,000 employees) from the United States and the United Kingdom. They found that less than half of their 400 respondents felt comfortable using people analytics to answer strategic questions (e.g. Are the right employees doing the right work to deliver our strategy?). Furthermore, less than half believed their organization is well equipped to do basic people analytics such as headcount analyses (43%) or producing organizational charts (39%). Other reports echo these findings. For example, Sierra-Cedar Inc. (2019) concluded that the vast majority of the organizations are still struggling to use advanced people analytics based upon their research among 1,892 organizations from a variety of countries and sectors. This is disappointing, as insights and recommendations from advanced analyses, such as root cause (e.g. regression), predictive and prescriptive analytics, are believed to be most effective for improving business outcomes (Cascio et al., 2019).

Currently, the academic literature on people analytics seems of little help to organizations looking to use people analytics effectively, because the literature is "not in a mature stage of development" (Fernandez & Gallardo-Gallardo, 2021, p. 177). The maturity stage is a result of people analytics being a relatively new research

area in which only 16 academic papers were published before 2016 (Qamar & Samad, 2021). The vast majority of these papers consequently focus upon the benefits people analytics could bring (80%), the barriers to adopting people analytics (60%), or the lack of analytical capacity within people analytics (60%) (Giermindl, Strich, Christ, Leicht-Deobald, & Redzepi, 2021). These three topics are related, as the capabilities required to conduct people analytics effectively is seen as one of the primary barriers organizations need to tackle to benefit from it (Angrave et al., 2016; Fernandez & Gallardo-Gallardo, 2021; McCartney, Murphy, & McCarthy, 2020). People analytics practitioners need a wide variety of competencies to be effective, but individuals who are proficient at statistics typically lack business acumen and HR knowledge and vice versa (Angrave et al., 2016; McCartney et al., 2020; Rasmussen & Ulrich, 2015). Consequently, Andersen (2016) argues that people analytics projects may suffer from poor analyses, address the wrong problems, or report biased and incorrectly interpreted results. However, even though the literature on people analytics explains why organizations may struggle, it provides little guidance on how to use people analytics effectively.

To fill up this gap, several practitioner-oriented books have appeared. Some provide hands-on support to execute advanced analyses (e.g. Edwards & Edwards, 2019; Levenson, 2015). As such, they address the analytical capability gap among people analytics practitioners. Other books describe how an effective people analytics function may be set up and present models to help practitioners establish an effective people analytics department (Ferrar & Green, 2021; Guenole et al., 2017). While these models provide guidance, they are not based upon systematic research. This is because most papers on people analytics are opinion pieces or literature reviews and rarely empirical in nature (Fernandez & Gallardo-Gallardo, 2021; Marler & Boudreau, 2017). This is problematic for three reasons. First, because the models are based upon anecdotal evidence, the authors may have missed crucial elements that explain how an effective people analytics function may be set up. In the "nine dimensions for Excellence in People Analytics model" of Ferrar and Green (2021), none of the dimensions, for instance, relates directly to ethics. If neglected, however, ethical misconduct in people analytics can have harmful effects on employees (e.g. losing their jobs, health damage) and the organization (e.g. reputation damage) (Giermindl et al., 2021; Tursunbayeva, Pagliari, Di Lauro, & Antonelli, 2021). Second, the models do not explain in-depth how the different elements are related. In the "workforce analytics operating model" of Guenole et al. (2017) ten elements are identified as critical to the way the people analytics function operates. However, it is unclear, for example, how the reporting structure of the function is related to the roles and responsibilities within the team. Third, the various models contain different elements. For example, whereas stakeholder management is emphasized within the "nine dimensions for Excellence in People Analytics model", it is absent in the "workforce analytics operating model". In reverse, project management was identified

by the "workforce analytics operating model", but missing from the "Excellence in People Analytics model". Considering that projects executed by a people analytics function should be managed, and stakeholders are the recipient of people analytics insights and recommendations, it is unclear why the different authors decided upon the inclusion of certain elements within their model. Based upon the previous, organizations require clarity on how an effective people analytics function can be created. This is the first challenge this dissertation addresses.

Aside from understanding what it takes for a people analytics function to be effective, it is also essential to explore its purpose. Currently, companies use people analytics insights and recommendations to enhance employee performance. They do this, for instance, by analyzing their employee data and firing workers who are flagged as unproductive in terms of packages delivered, messages sent, and the number of hours worked (Business Internet Tech, 2021; Ramishah Maruf, 2021; Soper, 2021). Additionally, others use people analytics in pursuit of employee well-being. Through people analytics they can for example find out what health programs are most beneficial to specific types of employees (e.g. depending upon their age or gender) and identify the antecedents of employee engagement (Cascio et al., 2019). Companies can furthermore use people analytics insights and recommendations in support of societal goals, such as equal treatment for men and women, different age groups and minorities (Coron, 2021; Logg, 2019). Logg (2019), for example, suggests that the algorithms produced by people analytics can reduce biases in hiring and selection decisions of seemingly irrelevant factors, such as employee height. Specifically, she notes that "even after controlling for the effect of gender and age, researchers found that taller people make more money. An inch in height is worth an additional $789 per year of salary" (Logg, 2019, p. 3). As people analytics insights and recommendations seem capable of supporting very different business results, and it is in the end focused upon employees and their data, it seems logical to look at the HRM literature to determine what its focus should be.

Business outcomes have traditionally been defined as financial gains within the HRM literature. This is in line with the shareholder perspective which is dominant in countries like the United States and United Kingdom (Paauwe, 2004). However, as organizational performance is a more distal outcome affected by other factors such as state of the economy, marketing, innovation, organizational structure and culture (P. F. Boxall, Purcell, & Wright, 2007; Levenson, 2015; Paauwe & Farndale, 2017), HR scholars typically focus upon the more proximal outcome of employee performance. As a result, much of the research describes how HR practices, such as employee development, performance management and rewards, can contribute to employee performance (e.g. Becker, Huselid, Huselid, & Ulrich, 2001; Campbell, 1990; Fey, Morgulis-Yakushev, Park, & Björkman, 2009; MacDuffie, 1995; Messersmith, Patel, Lepak, & Gould-Williams, 2011; Paauwe, 2004). One of the most popular models, the

Ability Motivation Opportunity (AMO) model of Appelbaum, Bailey, Berg, Kalleberg, and Bailey (2000), proposes that HR practices enhance the Abilities, Motivations and Opportunities employees need, which result in increased levels of performance (Appelbaum et al., 2000). Through the years, HR scholars found that HR practices impact employee performance via affective employee behavior, such as commitment, engagement, satisfaction and other forms of well-being (e.g. Baptiste, 2008; P. F. Boxall et al., 2007; Guest, 2017; Paauwe, 2004; van de Voorde, Paauwe, & van Veldhoven, 2012). As a result, employee well-being is considered as a way to increase employee performance within the HRM literature. However, an increasing number of HR scholars argue that well-being should not only be considered as a means towards an end, but also as an important business outcome in its own right (Beer, Boselie, & Brewster, 2015; Guest, 2017; Paauwe & Farndale, 2017). This perspective aligns with the multiple stakeholder perspective, traditionally dominant in Europe. According to this perspective, the interest of shareholders, managers, employees and the society as a whole should be considered as relevant business outcomes (P. F. Boxall et al., 2007; Paauwe, 2004; Paauwe & Farndale, 2017).

Due to globalization and an increasing focus upon corporate social responsibility, the emphasis on the shareholder perspective is slowly making way for the multiple stakeholder perspective (Battilana, Obloj, Pache, & Sengul, 2020; Paauwe, 2004). For HR scholars and practitioners, this implies they need to balance employee well-being and performance (Paauwe & Farndale, 2017). However, this appears to be a continuous challenge, as SHRM scholars found that what is good for the company, is not necessarily good for the employees (Peccei & van de Voorde, 2019; van de Voorde et al., 2012). While employees enjoy having autonomous, responsible, and meaningful jobs, having "too much of a good thing" hinders their performance (Lu, Brockner, Vardi, & Weitz, 2017; Pierce & Aguinis, 2013) Furthermore, if organizations push for employee performance through work intensification, this can harm employee well-being (Jackson, Schuler, & Jiang, 2014; Ogbonnaya & Nielsen, 2016; Peccei, van de Voorde, & van Veldhoven, 2013). As the relationship between employee performance and well-being seems complex, people analytics should be mindful of both outcomes. In line with the increasingly more widespread stakeholder perspective, I will therefore argue that people analytics should pursue employee well-being and performance outcomes within this dissertation.

As of today, there are few empirical studies that demonstrate how people analytics can provide insights and recommendations that support employee well-being or performance (Margherita, 2021). Therefore, the people analytics literature would benefit from "use cases" that demonstrate how it can support both outcomes. Such an use case may demonstrate, for instance, how a strategic HR initiative (like the implementation of agile way of working, which is a new working method among teams) affects employee well-being and performance within an organization. Moreover, it

may also be beneficial to demonstrate how people analytics insights can help to create jobs that make employees happy, healthy and productive (Peccei & van de Voorde, 2019). Consequently, the second challenge this dissertation will address is how people analytics can provide insights and recommendations that can be used to enhance well-being and performance outcomes.

Finally, this dissertation will address the earlier identified competency challenge among people analytics practitioners (Fernandez & Gallardo-Gallardo, 2021; Giermindl et al., 2021). This challenge relates to the fact that individuals who are proficient at statistics typically lack business acumen and HR knowledge and vice versa (Angrave et al., 2016; McCartney et al., 2020; Rasmussen & Ulrich, 2015). As a possible solution, it has been suggested that organizations and HR scholars may mutually benefit from a partnership on people analytics projects (Angrave et al., 2016; Simón & Ferreiro, 2018; van der Togt & Rasmussen, 2017). However, there appears to be a substantive gap between academics and practitioners in general (Pasmore, Stymne, Shani, Mohrman, & Adler, 2007) and closing this gap seems to be neither easy nor undisputed (e.g. Bailey, 2022; Guerci, Radaelli, & Shani, 2019; Rynes, Giluk, & Brown, 2007; Shani, Mohrman, Pasmore, Stymne, & Adler, 2007; Vosburgh, 2022). Likewise, some scholars claim that organizations interested in people analytics will not benefit from a collaboration with academia. According to Rasmussen and Ulrich (2015) this is because academics lack the business acumen required to ask the right questions that lead to effective people analytics projects (Rasmussen & Ulrich, 2015). However, thus far there are, to the best of my knowledge, no articles that discuss the potential benefits and challenges of such a partnership within people analytics in detail. Therefore, it is important to explore whether a collaboration between academia and organizations may be a viable strategy to help organizations tackle the competency challenge, which is one of the most important barriers to using people analytics effectively (Fernandez & Gallardo-Gallardo, 2021). This is the final challenge this dissertation will address.

Based on the previous, this dissertation addresses the following overall research question.

How can people analytics be used to gain insights into and provide recommendations to enhance business outcomes?

To answer this question, this dissertation will address the following sub-questions:

1. *How can an effective people analytics function be created?*
2. *How can people analytics be used to enhance employee well-being and performance?*
3. *How can people analytics departments benefit from a collaboration with academia?*

How can an effective people analytics function be created? (challenge 1)

For more than two decades, Sierra-Cedar has studied how organizations worldwide are using HR technology. As people analytics uses technology to analyze employee data (Marler & Boudreau, 2017), one of the topics Sierra-Cedar researches is the use of people analytics. In their most recent report, they showed that 29% of the 1,892 participating companies made use of descriptive analytics (e.g. benchmarking) and less than 20% made use of advanced people analytics (e.g. predictive analytics, machine learning and sentiment analyses) (Sierra-Cedar Inc., 2019). With regards to descriptive analytics, the research of Orgvue was slightly more optimistic. As mentioned before, approximately 40% of the 400 large organizations included in their sample used people analytics to aggregate data, headcount analyses, and other forms of descriptive analytics (Fernandez & Gallardo-Gallardo, 2021; Orgvue, 2019). Still, this is very disappointing, considering that the first article on people analytics appeared in 2003 (Marler & Boudreau, 2017) and that it has been marked as an important trend for over 7 years (Rasmussen & Ulrich, 2015). More importantly, advanced analytics appear to be crucial to providing insights and recommendations to improve business outcomes. This is because they can answer why employees behave in a certain way, predict what they may do, and provide recommendations on people-related decisions (Guenole et al., 2017; L. Liu, Akkineni, Story, & Davis, 2020). This means that the absence of advanced analytics still hinders the effectiveness of the people analytics function in most companies.

As a result, scholars have tried to answer "why we aren't there yet?" (Boudreau & Cascio, 2017; Minbaeva, 2017) and identified many obstacles that prevent people analytics practitioners from using advanced analytics (e.g. Fernandez & Gallardo-Gallardo, 2021). Moreover, they have developed various models to help practitioners become more effective at people analytics. Some of these models aim to help practitioners execute people analytics projects more effectively (e.g. Anger, Tessema, Craft, & Tsegai, 2021; Cascio et al., 2019; Guenole et al., 2017; Levenson, 2015). Others, however, describe the elements a people analytics function requires to be effective (e.g. Ferrar & Green, 2021; Guenole et al., 2017; Opatha, 2020; Shet, Poddar, Samuel, & Dwivedi, 2021). While the project-based models are useful, the effectiveness of the function seems to be more important. After all, if a people analytics function provides highly valuable insights or recommendations, it is more likely to receive, for example, additional funding and earns the trust of its stakeholders (Guenole et al., 2017).

However, as mentioned before, the current models that describe how an effective people analytics function can be established provide limited guidance. This is because they are based upon case studies from a single company, literature reviews, or are too practitioner-oriented. This is problematic for three reasons. First, the case studies

that developed a model on people analytics (i.e. Anger et al., 2021; L. Liu et al., 2020) have all approached people analytics from the context of a single company. As a consequence, these models focus on using people analytics to provide the HRM function with recommendations. However, people analytics is not "just for HR" as anyone who makes a people-related decision is argued to benefit from people analytics (see also Ferrar & Green, 2021). This implies that senior managers, board members, line managers and employees may be the recipient of people analytics too (Ellmer & Reichel, 2021; Guenole et al., 2017). Second, the models developed through literature reviews (i.e. Opatha, 2020; Shet et al., 2021) make use of a scanty amount of empirical studies on people analytics. Although the literature on people analytics has grown substantially within the last few years, very few studies have actually adopted an empirical approach to understanding people analytics (Qamar & Samad, 2021). Therefore, most studies seem to echo each other. In addition to this, these authors do not integrate lessons in their models from the broader and more advanced business intelligence literature of which people analytics is a sub-domain (Davenport & Harris, 2017; Holsapple et al., 2014). Consequently, these models seem to add relatively little to our understanding of what it takes to create an effective people analytics function. Third, although the practitioner -oriented models have generally been developed by scholars and practitioners working closely with people analytics practitioners in practice (e.g. Ferrar & Green, 2021; Guenole et al., 2017), the models have important limitations. Specifically, they seem to be developed based upon anecdotal evidence instead of an empirical validation process common to scientific research. Furthermore, although the models summarize what elements a people analytics function should focus upon to be effective, they remain relatively simplistic by not showing how the different elements within their model are for example related to each other. Therefore, it is difficult to draw up propositions from these models and develop an empirically grounded framework that addresses how an effective people analytics function may be created.

Seeing how the effective use of advanced people analytics barely increased in the last few years (Sierra-Cedar Inc., 2018, 2019) and the untapped potential this implies, this dissertation aims to synthesize (Chapter 2) and empirically explore (Chapter 3) how a people analytics function can effectively provide insights and recommendations to enhance business outcomes. Concretely, I will do this by first identifying the key ingredients people analytics needs to be effective based upon the people analytics and broader business intelligence literature (Chapter 2). By including insights from the business intelligence literature in this literature review, we can integrate lessons from the more advanced analytics sub-domains such as marketing and finance (Davenport & Harris, 2017), while also synthesizing the fragmented information within the people analytics literature (e.g. as evidenced by the existence of six models on people analytics that all consists of different elements). This leads to the development of the "People Analytics Effectiveness Wheel" as a heuristic model (Chapter 2). Second, this

dissertation will answer the call of Qamar and Samad (2021) and empirically explore how effective people analytics may look like in practice. I do this through in-depth interviews with members and stakeholders of the people analytics functions of large multinationals that have a reputation in the field of people analytics. In the end, this leads to the development of the "People Analytics Effectiveness Framework" in which the relationships between the elements and processes responsible for the effectiveness of a people analytics function are unveiled. Based upon this work, propositions will be developed (Chapter 3) which can be later tested in a large-scale survey research by other researchers. This latter is especially useful as people analytics is becoming increasingly more mainstream (Leonardi & Contractor, 2018), which means more organizations can participate in and benefit from this type of research.

How can people analytics be used to enhance employee well-being and performance? (challenge 2)

Born among the big tech firms from the USA, the shareholder perspective and its focus on (financial) performance is deeply ingrained within people analytics. Levenson (2015) for example, suggests that analytics should help organizations to achieve a competitive advantage that ultimately increases cash flow. Furthermore, many (academic) papers describe how people analytics insights can be used to save money (Ferrar & Green, 2021; Rosenbaum, 2019; e.g. Yuan et al., 2021), improve employee performance (Duhigg, 2016; Mulholland, 2018) and enhance the efficiency of HR practices (e.g. Chaudhary & Srivastava, 2021; Karwehl & Kauffeld, 2021). Throughout the years, various stories have appeared within the media of companies who have taken the focus on performance a bit too far. Bloomberg, for example, reports that "at Amazon, machines [algorithms] are often the boss – hiring, rating and firing millions of people with little or no human oversight" (Soper, 2021). In the article, multiple cases are described how the organization focused upon financial gains without taking the employee interest into consideration. For example, one contract driver got fired after 4 years by an algorithm for not being "productive enough". This is rated, among others, by how quickly employees can deliver packages, where they leave customers' packages, and how quickly they drive. Whether the customer is home or apartment complexes are closed is not considered (Soper, 2021). Similarly, the Russian small tech firm Xsolla recently made headlines by informing 147 of their 500 employees that they were fired as the "big data team" from the company had judged they were "non-involved and non-productive" based upon how their computers and e-mail accounts were being used (Business Internet Tech, 2021).

Although cases like these are fortunately rare, they do emphasize that it is important to consider the interest of multiple stakeholders when providing insights and recommendations with people analytics. As mentioned before, within this dissertation, I will focus in line with the multiple stakeholder approach upon how

people analytics insights and recommendations can be used to benefit the employer and employee (e.g. Beer et al., 2015; Paauwe & Farndale, 2017). In order to illustrate how people analytics can serve both interests at the same time while still being strategical and valuable, I will conduct two "use case" (i.e. example) studies. This is important because it is primarily the bad examples that make the headlines. Therefore it is little surprising that some stakeholders, like HR leaders, may feel hesitant about people analytics (Fernandez & Gallardo-Gallardo, 2021).

First, I will demonstrate how people analytics can be used to evaluate whether the decision of a company to adopt the agile way of working is beneficial to employee well-being and performance (Chapter 4). The agile way of working is characterized by self-management, face-to-face communication, reflexivity, a quick product turnaround and customer interaction and originated within the Information Technology sector (Beck et al., 2001). Although there is anecdotal evidence from large tech firms like Netflix and Spotify that the agile way of working leads to beneficial team outcomes (Rigby, Sutherland, & Noble, 2018), non-tech firms are implementing it currently at a rapid rate expecting the same beneficial results for all their teams regardless of their functional domain (Edmondson & Gulati, 2021; Mergel, Gong, & Bertot, 2018). Therefore, I will use people analytics to assess whether the agile way of working is indeed beneficial to employee performance and well-being. Using these insights, business leaders can (re)-evaluate their strategic decision to use the agile way of working based upon data rather than beliefs and anecdotal evidence.

Second, I will assess how people analytics can be used to provide insights and recommendations to HR practitioners (Chapter 5). Specifically, I will investigate whether employees experience complex trade-off patterns in which well-being and performance co-occur. This is in line with the SHRM literature, which showed that some low performing employees may, for instance, feel highly satisfied with their job and vice versa (e.g. Ayala, Silla, Tordera, Lorente, & Yeves, 2017; Peiró, Kozusznik, Rodríguez-Molina, & Tordera, 2019). The combinations in which employee well-being and performance may co-occur within a person can also be called employee well-being and performance profiles (Peccei & van de Voorde, 2019). For each profile, I will assess whether it is related to various job demands (e.g. work pressure) and resources (e.g. autonomy) to provide data-driven insights on how work may be designed to increase the amount of employees who have a profile characterized by high well-being and high-performance.

How can people analytics departments benefit from a collaboration with academia? (challenge 3)

As mentioned before, the large amount of skills people analytics practitioners require seem to be one of the main obstacles for organizations to use people analytics effectively (Fernandez & Gallardo-Gallardo, 2021; McCartney et al., 2020). This is because HR professionals usually fall short on statistical skills and statistically strong individuals usually lack business acumen and HR knowledge (Andersen, 2016; McCartney et al., 2020; Rasmussen & Ulrich, 2015). As a result, there have been many debates about how the ideal people analytics practitioner may be developed (Angrave et al., 2016; McCartney et al., 2020; Rasmussen & Ulrich, 2015; van der Togt & Rasmussen, 2017). Among these, a collaboration with academia has been suggested as a possible solution (Minbaeva, 2018; Simón & Ferreiro, 2018; van der Togt & Rasmussen, 2017). This is because HR academics typically have the required theoretical knowledge to build sound conceptual models, the statistical capabilities to conduct the analyses, and sufficient knowledge to interpret the results (e.g. Andersen, 2016; Angrave et al., 2016; Cascio et al., 2019; Simón & Ferreiro, 2018). Simón and Ferreiro (2018) display one of the rare accounts that show the results of such a collaboration on people analytics. Specifically, the authors investigated what factors contributed, among others, to store profit for a large fashion company. Based on their analysis, they found that the presence of a store manager more than doubled the potential sales of a store per square meter and what the optimal percentage for voluntary turnover was for the organization in question (Simón & Ferreiro, 2018). In sum, these results demonstrate that teaming up with academia may indeed provide organizations with relevant people analytics insights.

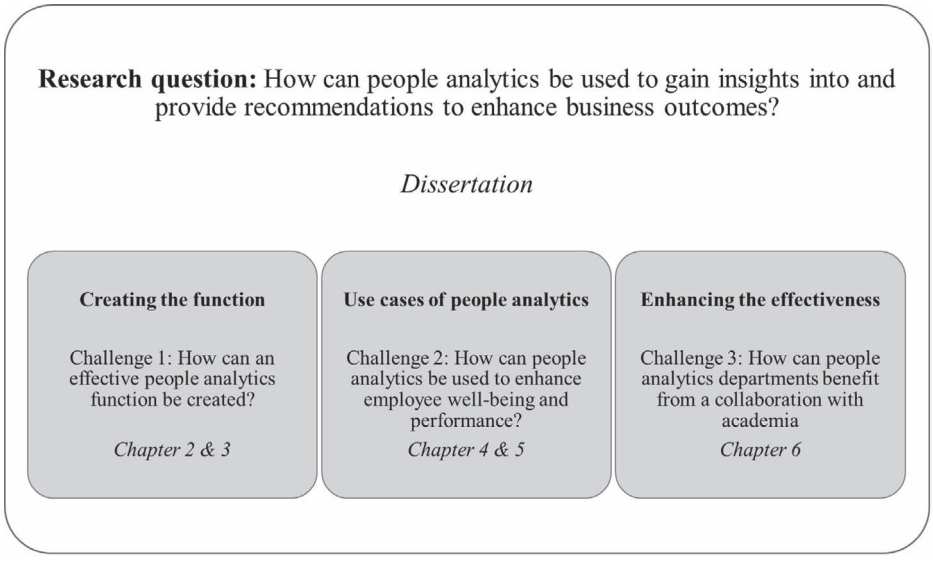
Outside of the narrow focus of the people analytics domain, it has been suggested that a collaboration between an organization and academics may indeed pay off. On the one hand, academics can help organizations to bring academic rigor, validation, external support and credibility to projects they collaborate upon (Zhang, Levenson, & Crossley, 2015). On the other hand, academics seem to benefit from a partnership in four ways. First, it increases the likelihood that their research findings are used in practice (i.e. impact) (Beer, 2020; Guerci et al., 2019; Simón & Ferreiro, 2018). Second, it provides academics with normally difficult to acquire datasets (e.g. large, longitudinal datasets from multiple actors) (Zhang et al., 2015). Third, papers resulting from collaborative research are typically cited more often by other scholars (Shani et al., 2007). Fourth, collaborative research allows academics to explore relatively new and underexplored areas that lack empirical research (Adler & Beer, 2007). However, while there is the promise, there is also skepticism. A common complaint about collaborative research with organizations is that one may wonder if academics do not simply become management consultants for the company when carrying out the analyses displayed above (Guerci et al., 2019; Kilduff, Mehra, & Dunn, 2011). Moreover,

one can also question whether these insights are truly academically relevant and whether the research team was able to maintain their objectivity despite working closely with the organization (Guerci et al., 2019; Pasmore et al., 2007).

Based upon the previous, it thus seems to be beneficial as well as challenging for practitioners and academics to collaborate. However, thus far academics have primarily focused upon either the benefits or the challenges when discussing it as a possible solution for the competency gap within people analytics. Therefore, the benefits and challenges in the context of people analytics will be addressed for both parties in this dissertation. Specifically, I will describe the benefits, challenges and ways to navigate through these challenges, based on my own experiences in pursuing a joint PhD trajectory between academia (Tilburg University) and a people analytics department of a large financial organization. Moreover, I will describe how the involved people analytics department became more effective over time by having access to the competencies of the research team and their department (Chapter 6).

Figure 1 presents an overview of the different sub-questions that are addressed in this dissertation.

Figure 1. Overview of this dissertation



Dissertation outline

The research questions will be addressed through one conceptual and four empirical chapters (see Table 1 for an overview). These chapters are structured as follows:

In **chapter 2,** the key ingredients a people analytics team requires to effectively provide insights and recommendations to increase business outcomes will be explored. Specifically, a narrative literature review will be conducted that synthesizes the fragmented people analytics and business intelligence literature to come to a comprehensive understanding of the enabling resources, products, stakeholder management and governance structure a people analytics team needs.

Chapter 3 focuses on creating an effective people analytics function through qualitative research. Through 36 in-depth interviews with members of people analytics functions and their stakeholders, the inputs, processes, and outputs a people analytics function requires to produce insights and recommendations that enhance business outcomes in nine different organizations are investigated. This chapter focuses on developing an empirically grounded framework and propositions that address how an effective people analytics function can be created. To this end, it examines 1. the relationship between the different elements a people analytics requires, 2. provides insight into the inputs, processes, and output a people analytics function requires to be effective, and 3. included the recipients of these outputs, the stakeholders of a people analytics function.

In **chapter 4** the focus switches to the second sub-question and presents a use case on how people analytics can provide insights that can be used to enhance well-being and performance. As mentioned before, organizations are currently implementing the agile way of working based upon a belief that this leads to beneficial team outcomes. However, there is limited empirical evidence for this claim within the IT-sector from which it originated, let alone across different functional domains. Therefore, chapter 4 investigates in a large multinational firm operating in the financial sector whether the agile way of working is indeed related to increased team engagement and performance like the organization expects. Furthermore, this chapter assesses whether psychological safety climate mediates these relationships.

Chapter 5 presents another people analytics use case. Specifically, it describes whether different employee performance and well-being profiles exist among employees within the Dutch division of a multinational bank. Employee performance and well-being profiles refer to specific combinations in which employee well-being and performance co-occur among employees, such as high well-being/low well-being and high well-being/high well-being. Moreover, to provide recommendations to the organization about how the number of employees with favorable well-being and performance profiles can be facilitated, it is also studied whether seven job resources and demands are related to different profiles.

Table 1. Overview of the chapters in this dissertation

Chapter	Title	Goal and contribution	Research type	Key issue
1	Introduction	**Introduce** the topic of the dissertation, its relevance, and its outline.	N/A	
2	People Analytics effectiveness: Developing a framework	**Identify** based upon the existing literature what key ingredients a people analytics department requires to contribute to organizational performance and **develop** a people analytics effectiveness framework.	Literature review	1
3	The road to people analytics effectiveness: A qualitative exploration of the inputs, processes, and outputs.	**Explore** which the inputs, processes, and outputs a people analytics function requires to be effective and **establish** an empirically grounded framework on the topic.	Qualitative research	1
4	The effects of the agile way of working on team performance and engagement	**Examine** whether the agile way of working contributes to team performance and engagement, and **study** whether psychological safety climate mediates these relationships.	Quantitative research	2
5	Exploring the Nature and Antecedents of Employee Energetic Well-Being at Work and Job Performance Profiles	**Assess** whether employees can be **classified** according to their perceived well-being and performance combinations and **assess** which job demands and resources relate to specific performance and well-being combinations.	Quantitative research	2
6	Bridging the gap: How a shared PhD trajectory can benefit practice and academia to advance people analytics	**Describe** the benefits and challenges of conducting a joint PhD trajectory to advance the maturity of a people analytics team	Ethnographical research	3
7	Discussion	**Conclude** by answering to the central research question, discussing the practical and theoretical implications, and limitations of this dissertation	N/A	

In **chapter 6** I address the final sub-question of this dissertation by discussing based upon my own experience of working for 4,5 years in a joint PhD trajectory the benefits and challenges when academia and organizations collaborate upon people analytics. In response to the challenges, ways to navigate through these challenges are also presented. Furthermore, it is discussed how the people analytics department has developed throughout this time and illustrated how our partnership has helped to make the people analytics department within our partner organization more effective.

In **chapter 7** I will answer the main research question of this dissertation: "How can people analytics be used to enhance employee well-being and performance?" by providing the main conclusions of the three sub-questions. Furthermore, I will also summarize and discuss the findings of the previous chapters and provide suggestions for future research on people analytics. Finally, I will discuss its limitations and conclude with the implications of this dissertation for research and practice.

Scientific relevance

This dissertation aims to advance the scientific understanding of using people analytics in three ways. First, as noted by Qamar and Samad (2021) there is still a rather limited understanding of what it takes to execute people analytics effectively. Fernandez and Gallardo-Gallardo (2021) echo this sentiment and suggest scholars should provide "vision and leadership" (p. 178) on how organizations may use and implement people analytics. Therefore, this dissertation aims to describe and empirically assess how an effective people analytics function can be created. Second, my dissertation will answer the call to conduct more empirical research on the topic of people analytics (Marler & Boudreau, 2017; Qamar & Samad, 2021; Van der Laken, 2018), and specifically on how people analytics insights and recommendations could support employee well-being and performance (Margherita, 2021). I will aim to do this by conducting two people analytics use cases. Furthermore, these use cases will also add to the teams and SHRM literature, by exploring two relatively new research topics. Specifically, I will assess if the agile way of working is beneficial to team outcomes in different functional domains (e.g. Hobbs & Petit, 2017). In addition, I will study through a person-centered approach whether employees can be clustered into different well-being and performance profiles (e.g. Ayala et al., 2017; Tordera, Peiro, Ayala, Villajos, & Truxillo, 2020) and investigate possible antecedents of these well-being and performance profiles. Third, I aim to contribute to the debate about a collaboration between organizations with academia to reduce the competency gap within people analytics (Fernandez & Gallardo-Gallardo, 2021; McCartney et al., 2020). I will do this by building upon my own experience of working in a joint PhD trajectory in which a department of a university and a large organization operating in the financial sector collaborated. Specifically, I will discuss its benefits, tensions and ways to navigate through these tensions to inform academics and practitioners

interested in such partnerships in the future. By doing this, I also aim to contribute to the literature on collaborative research (e.g. Guerci et al., 2019; Shani et al., 2007; Zhang et al., 2015). I will do this by illustrating how the potential "good practice" on collaborative research, a joint PhD trajectory (Guerci et al., 2019), may work out in practice.

Practical relevance

As illustrated by the examples within this introduction, organizations have much to gain by establishing people analytics departments (Davenport & Harris, 2017; Ferrar & Green, 2021; Guenole et al., 2017). Despite significant investments though, the number of organizations that have established a people analytics department capable of providing (strategic) insights and recommendations to enhance business outcomes is low (Ledet et al., 2020; Orgvue, 2019; Sierra-Cedar Inc., 2019). In order to help organizations become more effective at people analytics, this dissertation strives to provide practitioners with some clear, scientifically validated guidelines on how to set up an effective people analytics function. This is the first contribution of this dissertation. Second, I will illustrate the types of insights and recommendations people analytics may provide for enhancing employee performance and well-being. Specifically, I will illustrate how a people analytics project may be used to support the strategic initiatives of a company (i.e. to implement the agile way of working) and show how it may guide the HR policy and specifically on how to design work (e.g. by studying employee well-being profiles and their antecedents). Lastly, I will provide practical insights and guidance on how people analytics departments may partner with academia to reduce their competency gap and enhance their effectiveness.

2

People Analytics effectiveness: Developing a framework

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Abstract

Purpose: The purpose of this paper is to explore the key ingredients that people analytics teams require to contribute to organizational performance. As the information that is currently available is fragmented, it is difficult for organizations to understand what it takes to execute people analytics successfully.

Design/methodology/approach: To identify the key ingredients, a narrative literature review was conducted using both traditional people analytics and broader business intelligence literature. The findings were summarized in the People Analytics Effectiveness Wheel.

Findings: The People Analytics Effectiveness Wheel identifies four categories of ingredients that a people analytics team requires to be effective. These are enabling resources, products, stakeholder management, and governance structure. Under each category, multiple sub-themes are discussed, such as data and infrastructure, senior management support, and knowledge, skills, abilities and other characteristics (KSAOs) (enablers).

Practical implications: Many organizations are still trying to set up their people analytics teams, and many others are struggling to improve decision-making by using people analytics. For these companies, this paper provides a comprehensive overview of the current literature and describes what it takes to contribute to organizational performance using people analytics.

Originality/value: This paper is designed to provide organizations and researchers with a comprehensive understanding of what it takes to execute people analytics successfully. By using the People Analytics Effectiveness Wheel as a guideline, scholars are now better equipped to research the processes that are required for the ingredients to be truly effective.

Keywords: People analytics, HR analytics, Workforce analytics, Organizational performance.

Paper type: Viewpoint

Introduction

The human resource management (HRM) function is making steps to combine its intuition, experience, and beliefs with the new trend of data analytics (Rasmussen & Ulrich, 2015; van der Togt & Rasmussen, 2017). Marler and Boudreau define people analytics (data analytics applied to human resources [HR]) as "a HR practice enabled by information technology that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organizational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making" (2017:15). People analytics can thus be used to solve pressing business issues, as illustrated, for example, by the people analytics team of ING. The bank was looking to recruit specialists to work on Know Your Customer (KYC). This covers transaction screening; client file enhancement, including documentation and data as well as identity verification; and structural solutions to execute the bank's KYC policies – all ultimately focused on protecting the bank from financial economic crime. However, due to the shortage of people with the necessary skills required for these roles in the global labor market, ING's people analytics team worked to identify which internal ING employees would be suited to fulfill the vacancies at the KYC department. To do so, they matched over 9,000 different job titles to an external database, which afforded them a global overview of the knowledge, skills, and abilities of their entire employee population. They were consequently able to determine which employees would fit the profile of the vacancies well, and conversations with those employees ensued. This not only allowed the company to fulfill critical vacancies, but also provided internal employees the opportunity to develop themselves into new roles that they may otherwise have never imagined.

Although other companies are also reaping the benefits of people analytics, only 16% of organizations have actually implemented advanced people analytics in practice (Sierra-Cedar Inc., 2018). This low adaptation rate has caused an academic discussion on the many issues that people analytics is facing in practice (e.g. as reported in a special issue of this journal[1]). Given the growing interest in the area, we believe that the development of a heuristic framework based on the currently available (people) analytics literature is both timely and an important first step to gain a more in-depth understanding of what it takes to establish a successful, advanced analytics team.

By developing this framework on people analytics effectiveness, we contribute to theory as well as practice in three distinct ways. First, although many scholars have discussed key ingredients that are required for a people analytics team in the past (e.g. Andersen, 2016; Green, 2017; Guenole et al., 2017), this information is often fragmented and focused almost exclusively on people analytics. However, considering that other sub-domains of business intelligence fields, such as marketing and customer analytics, are more advanced than people analytics (e.g. Davenport & Harris, 2017;

Holsapple et al., 2014), the knowledge from these other sub-domains may provide us with new insights into how to establish an effective people analytics team. We will consequently review both people analytics and business intelligence literature to develop our framework.

Second, while the enablers and (potential) products of a people analytics team have been the focus of various articles (e.g. Green, 2017; Hota & Ghosh, 2013), many questions related to ethics and compliance remain largely unanswered (Van der Laken, 2018). Considering that people data is increasingly regulated by law and the number of ethical questions regarding the usage of people analytics is growing, we believe this to be a lacuna in the people analytics literature. Therefore, this paper also investigates what ingredients should be in place for a people analytics team to achieve both compliance and legitimacy in the eyes of internal and external stakeholders.

Third, we make a contribution to the discussion that is taking place in practice about what it takes for a people analytics team to be successful. While it is, for instance, common practice to evaluate people analytics teams based on their maturity level (e.g. Bersin and Associates 2012, as cited in Bersin, 2012), the underlying assumption to these models is that the more complex a team's analyses become, the more mature the team is and thus the more value it can add to an organization. However, we believe this assumption is troubling for two reasons. First, as organizations have reported to gain the most added value from their people analytics teams through descriptive analytics (i.e. 80% at Shell, van der Togt & Rasmussen, 2017), this linear way of thinking about the maturity level of people analytics appears to be incorrect when the added value of the team is concerned. Second, it is highly likely that more aspects of a team than just the complexity of its analysis affect its potential added value. For instance, while the statistical skills of a team may be excellent, stakeholder knowledge of statistics may be insufficient to understand the insights that the team provides, which causes the team to have limited added value. Therefore, we believe it is time to explore the many different ingredients that can lead to the success of a people analytics team instead of solely the complexity of the analysis.

Methods

To identify which ingredients are critical for a people analytics team, we conducted a narrative literature review in two steps. In the first step, we searched for literature relevant to the topic of people analytics effectiveness. We consequently did not review every people analytics or business intelligence paper, but analyzed the most relevant texts in depth. To find relevant articles, we searched for English or Dutch literature using online databases. We specifically used keywords such as "people analytics," "HR analytics," "workforce analytics," "talent analytics," and "business intelligence" and keywords reflecting sub-fields, such as "finance analytics" and

"marketing analytics." Furthermore, as people analytics is a relatively new research field, we did not specify a time frame for our search using the first four search terms. For both the business intelligence literature and the sub-fields in particular, we specified that articles needed to be published after 2005. This was done to narrow our search in this relatively older and larger research fields. Thereafter, we employed the snowball technique to find additional relevant literature using the reference list of the literature that we found.

In the second step, we read the search results in detail and assigned codes to each of the ingredients that we encountered that are required for people analytics to be effective. Based on our coding scheme and discussions among the authors of this paper, four different categories of ingredients emerged from the literature: 1) the "enabling resources" of a people analytics team, 2) the "products" the team delivers to the organization, 3) the main "stakeholders" who should be at the receiving end of these products in order to add value to the organization, and 4) the "governance structure" that a people analytics team requires to achieve compliance and legitimacy. Based on the literature, as each category appeared to be critical to the success of a people analytics team, we decided to structure our paper around these four categories. Therefore, in the next section, we focus on discussing the ingredients in more detail in relation to the following questions:

1. What are the enabling resources of a people analytics team?
2. What types of products should this team deliver to contribute to organizational performance?
3. Who are the stakeholders of this team, and how should they be managed?
4. What are the elements of a people analytics team's proper governance structure to safeguard compliance and achieve legitimacy?

The enabling resources of a people analytics team

In the literature, a number of ingredients can be identified that a people analytics team needs in order to be effective. These are 1) senior management support; 2) data and infrastructure; and 3) the knowledge, skills, abilities, and other characteristics (KSAOs) of people analytics staff (e.g. Andersen, 2016; Green, 2017; Marler & Boudreau, 2017).

Senior management support: According to various scholars (e.g. Davenport & Harris, 2017; Green, 2017; Guenole et al., 2017), support of senior management is one the main prerequisites for an analytical team to be successful. This is because senior management is capable of providing the team with both financial resources and political support. With financial resources, the team can invest in the required equipment, IT infrastructure, and people, which together make up the people analytics team. With political support, senior management sends signals to other stakeholders,

such as line management and HR professionals, that analytics is important and that data-driven decisions are the future (Davenport & Harris, 2017; Guenole et al., 2017). Guenole et al. (2017) consequently recommend close involvement of the HR director (the highest ranking HR leader of the company) in a people analytics team and full support from senior leadership outside of the HR function. If such support cannot be achieved, then they warn that the team will likely encounter more resistance from other stakeholders. Internal support from senior management thus appears to be highly important for an effective people analytics team.

Data and IT infrastructure: Data is at the core of the people analytics function (Davenport & Harris, 2017; Guenole et al., 2017) and is required for a team to conduct analyses and report insights. People analytics may work with various data types, such as traditional HR data (i.e. absenteeism and surveys); business data (i.e. performance) (Edwards & Edwards, 2019); or newer types of data that are, for instance, obtained through personal devices such as location and health (Boudreau & Cascio, 2017). The data that a team uses may exist in various forms, such as structured, unstructured, longitudinal, cross-sectional, qualitative, or quantitative (Edwards & Edwards, 2019; Guenole et al., 2017; Holsapple et al., 2014; Van der Laken, 2018).

Although the quantity of data appears to be less of an issue now that much more data than ever before is available from workers (Boudreau & Cascio, 2017), the quality of the data is still a reason that many projects fail, according to Andersen (2017). This is also captured in the popular phrase "garbage in, garbage out" (Andersen, 2017:134), which means that erroneous data will also likely result in erroneous findings. There generally appear to be three major reasons that people analytics teams struggle with low data quality. The first reason is the absence of one overarching database (Barton & Court, 2012), which means that the data the team receives can be out of date. Second, data is often the result of human input, which means that it can be incorrect or incomplete. The third reason is that one concept may have various data definitions in different areas (divisions or subsidiaries) of a business. This can be an especially complex problem once an organization operates in several countries: For example, a full-time workweek is already considered to consist of a different amount of working hours in different countries (e.g. Eurostat, 2013). To cope with the issue of data quality, cleaning the data from errors is considered to be an important, but time consuming task of a people analytics team (Britnell 2016, as cited in Green, 2017). In practice, this means that a team may spend up to 25–30% of its time cleaning the data to provide an organization with correct and credible results (Davenport & Harris, 2017).

With regard to IT infrastructure, Marler and Boudreau (2017), among others (e.g. Barton & Court, 2012; Bose, 2009; Trkman, McCormack, De Oliveira, & Ladeira, 2010), argue that it should be capable of storing and processing a sufficient data

quantity and quality and sharing the results with decision-makers. However, this is challenging in many organizations as old IT systems prevent data from being integrated into one system due to siloed information (Barton & Court, 2012) and, as previously mentioned, the absence of shared definitions (Guenole et al., 2017). Although aligning these systems is a time-consuming process, it seems crucial that the IT infrastructure is of high quality for efficiency and the credibility of the results. Furthermore, according to Boudreau and Cascio (2017), it is also important that the right communication channels, techniques, and timing are used when sharing information with decision-makers as this can motivate them to act on the insights provided by a people analytics team. Bose (2009) and Boudreau and Cascio (2017) state that the key elements in this regard are that the information provided should be aligned to the business strategy and that easy-to-access information should be delivered to decision-makers on demand. In practice, this means that any manager will have real-time access to his or her current people KPIs on which to base decisions. All in all, it can thus be concluded that having high-quality and sufficient data, a high-quality IT infrastructure, and a communication infrastructure that is both efficient and impactful is critical for an effective people analytics team.

The KSAOs of people analytics staff: In the literature, the question of which KSAOs the experts of a people analytics team require is highly debated. Rasmussen and Ulrich (2015), for instance, argue that it is easier to teach HRM and related theories to people with strong statistical skills than the other way around, whereas Levenson (2005) cautions against hiring people with a lack of HRM knowledge because these people may draw the wrong conclusions about their findings, as not all HRM activities can be expressed in numbers. The current consensus on the topic is that for a people analytics team, strong HRM or psychological and statistical skills lead to the most effective teams. In the popular six-competency model of Andersen (2016), these two skills, in addition to storytelling, visualization skills, business acumen, and strong data management skills, are seen as must-haves for people analytics teams. In 2017, Green added a seventh competency to this model, namely, change management, as he believes that teams should also ensure that their insights are successfully implemented in the organization. In addition to this, Davenport and Harris (2017) specifically mention stakeholder management capabilities in general as a core capability for a people analytics team. At least eight different KSAOs consequently appear to contribute to the effectiveness of a people analytics team.

The types of products that a people analytics team should deliver to contribute to organizational performance

Based on the literature, a people analytics team may offer three broad types of products to an organization in order to improve decision-making. These are 1) the development of employee monitoring tools, 2) organizational research, and through

these, 3) establishing an evidence-based culture (e.g. Angrave et al., 2016; Marler & Boudreau, 2017)

Employee monitoring tools: Within the field of people analytics, one of the most common practices is to report basic information about personnel, such as the number of Full Time Employee's (FTEs) and absenteeism ratios (van den Heuvel & Bondarouk, 2017). The two most well-known employee monitoring tools are dashboards and scorecards (Angrave et al., 2016; Marler & Boudreau, 2017), which often contain historical data (Angrave et al., 2016), survey scores, and benchmarking information (Davenport & Harris, 2017). According to Holsapple et al. (2014), these types of products can facilitate the identification of problems, share insights, facilitate decisions, and spur stakeholders into action. A number of companies have reported that these descriptive statistics added the most value to their organizations (van der Togt & Rasmussen, 2017). However, organizations have often not tested whether the concepts that they report truly have a relationship with important performance indicators (Levenson, 2005). Thus, it can be debated whether decision-makers are truly receiving the information they require to make the best decision possible. It therefore seems important to test the strategic relevance of the information contained in the reports to add the most value to an organization through this type of service (Bose, 2009).

Organizational research: Kaur and Fink (2017) and Levenson and Fink (2017) describe conducting organizational research as an important delivery for a people analytics team. Organizational research can be defined as the "studies or experiments conducted to address a specific, one-off organizational question" (Kaur & Fink, 2017:15). By carrying out such research, organizations have, for instance, examined what the most important predictors are of team satisfaction, collaboration, and performance for their specific organization (e.g. Google's project Aristotle). The benefit of this organization-specific research is that one can investigate the topics most relevant to an organization (Kaur & Fink, 2017), and the results can provide contextualized, specific insights. To conduct any organizational research, a people analytics team must first develop analytical models. Three types of analytical models can be distinguished in the literature, with three unique purposes. The first is the behavioral model, which uses existing data to establish causal relationships between predictors and the desired outcomes (Levenson, 2005). This type of model could, for instance, be used to determine the KSAOs that are related to high performance, which a recruiter may then use to make hiring decisions. The second model is the predictive model, which utilizes existing data to predict future outcomes (Levenson, 2005). In comparison to the previous model, this model may predict which of the applicants is most likely to become a high performer. The third model, a prescriptive model, also uses existing data but prescribes to decision-makers the action they should take (Halo, no date). In this case, the model would tell a recruiter which

applicant he or she should hire. Specific to predictive and prescriptive models is that they can make use of machine learning and artificial intelligence (AI) (Guenole et al., 2017; Halo, no date). Machine learning and AI are both designed to autonomously identify patterns in large, complex bodies of data, such as text analysis (i.e. natural language processing). However, although AI is far more efficient than a human at analyzing text, it has also been reported to lack in accuracy (Kaur & Fink, 2017). In addition, van den Heuvel and Bondarouk (2017) state that machine learning models do not necessarily consider causal relationships when making their predictions. Therefore, they indicate that this type of model building can best be done with many variables and when studying complex relationships. However, this does not come without risk, as the data analyst may no longer understand why a certain prediction or prescription is made by the model (e.g. Amazon's recruitment algorithm that discriminated against women (Dastin, 2018)). It can consequently be argued that the creation of the three analytical models and the exact methods used by these models should be considered based on their specific use-case. After all, each model is likely able to improve people's decisions in their own way and is thus capable of adding value to an organization. Therefore, an effective people analytics team is capable of not only building all three different models, but also selecting the most appropriate model for the organizational question at hand.

Establishing an evidence-based culture: One of the most important goals of the analytical function is to establish a culture in which (personnel's) decisions are being made based on analytics and data (e.g. Davenport & Harris, 2017). As the core task of a people analytics team is to analyze and share data-driven insights about employees, that team is a vital element in the establishment of this culture. However, as Guenole et al. (2017) stress, an evidence-based culture also helps to ensure that stakeholders act on the insights provided by a people analytics team instead of ignoring them. This point is supported by Davenport and Harris (2017), who state that a culture in which stakeholders actively search for, understand, use, and act on the insights provided by people analytics helps to make those teams prosper and grow. After all, once the use of data and analytics becomes more common practice, stakeholders will likely value their outputs more, which also further increases the power and reputation of the team. As such, the establishment of an evidence-based culture will likely directly influence the effectiveness and added value of people analytics teams.

Aside from delivering relevant, high quality, and data-driven products, Davenport and Harris (2017) state that support from senior management is crucial to establish an evidence-based culture. In particular, support from the CEO, senior management, and senior leaders serving as role models are mentioned as critical success factors. The reason for this is that once senior managers push for the use of analytics, the attitude and mindset of other stakeholders, and particularly their subordinates, may

change as well. It consequently appears that both the people analytics team and senior management are crucial factors in establishing an evidence-based culture.

The stakeholders of a people analytics team and the way in which they should be managed

In the literature, stakeholder groups are classified in numerous ways. Davenport and Harris (2017) distinguish the various stakeholders of a team by their functional role, whereas Guenole et al. (2017) group stakeholders based on the relationship they have with their people analytics team (e.g. customers, gatekeepers, and those impacted by the results). As membership in these groups is not mutually exclusive (Guenole et al., 2017), and since different stakeholders within the same group likely have varying interests and needs (e.g. line managers and employees are grouped in the same category), we have opted for classification in functional groups. We therefore discuss the following groups as the main stakeholders of a people analytics team: 1) HR professionals, 2) management (senior management and line management), 3) employees and their representatives, and 4) other analytical teams (e.g. Guenole et al., 2017; van den Heuvel & Bondarouk, 2017).

HR professionals: As people analytics teams generally focus on generating insights into the workforce, HR professionals are often seen as the most important stakeholders of a people analytics team. For HR professionals, people analytics allows them to demonstrate the impact of their initiatives on business outcomes (Mondore, Douthitt, & Carson, 2011) and to combine their intuition with objective data and analytical insights to make better decisions (Rasmussen & Ulrich, 2015). In summary, people analytics can be seen as "HR (analytics) for HR" (Guenole et al., 2017), and HR professionals may therefore be the ones who could potentially benefit the most from having an effective people analytics team. However, as stated in the introduction, HR professionals are often not attracted to data and appear to be uncertain about how to utilize it (i.e. Angrave et al., 2016; Marler & Boudreau, 2017; Rasmussen & Ulrich, 2015), which hinders the adaptation of people analytics and limits the value a company can gain from analytical insights (Levenson, 2011; Marler & Boudreau, 2017). To solve these issues, an often-noted recommendation for effectively involving this stakeholder group is to educate its members on analytics and make it part of their DNA (Green, 2017; Minbaeva, 2018). Moreover, the following have been recommended: sharing success cases, focusing on topics that are truly relevant for HR professionals, analyzing HR practices and metrics associated with business issues and performance, and ensuring that HR professionals become part of the analytical process from the beginning (Guenole et al., 2017). It can consequently be concluded that HR professionals are not only some of the most important stakeholders of a people analytics team, but also a group that requires special attention from the team to become truly successful. As people analytics can only be

effective when stakeholders act on the insights gleaned from it, successfully managing HR professionals seems crucial for a successful people analytics team.

Senior management: As mentioned previously, the support of senior management is seen as an enabler of an effective people analytics team. While senior management can help highlight the importance of people analytics to other stakeholders (Davenport & Harris, 2017; Smeyers 2016 as cited inGreen, 2017; Guenole et al., 2017), it also comprises important customers for the team. By providing senior managers with relevant insights and recommendations, they can tackle pressing organizational issues and execute the business strategy *(van den Heuvel & Bondarouk, 2017; van der Togt & Rasmussen, 2017).* To do this successfully, having regular conversations with them is recommended to understand their needs and share the insights and recommendations in a way that can be easily understood, communicated, and acted upon *(Guenole et al., 2017; van der Togt & Rasmussen, 2017).* Moreover, by paying special attention to the "so what" question, *van der Togt and Rasmussen (2017)* argue that stakeholders, such as senior and line management, can be spurred into action. This is crucial for effective people analytics teams, as they can add value to an organization only when their insights and recommendations are acted upon.

Line management: Whilst HR professionals and senior management often create the overall personnel policies, line managers are generally tasked with their implementation and execution (i.e. P. F. Boxall et al., 2007; P. Wright & Nishii, 2012). Guenole et al. (2017) consequently argue that line managers are the ones affected by the findings of a people analytics team as they are likely to be the ones tasked to act on those findings (e.g. provide a salary increase to top performers to decrease voluntary attrition). In line with this, Levenson (2005) argues that line managers, similarly to HR professionals, should be the ones who own the change process – not a people analytics team – after people analytics provides them with the required insights. van den Heuvel and Bondarouk (2017) argue, however, that many line managers have difficulty making decisions based on data. In particular, they report that line managers "find it hard to understand, accept and adopt the application of analytics in decision making" (van den Heuvel & Bondarouk, 2017:14). Guenole et al. (2017) argue that this resistance makes sense when line managers are asked to give up their decision-making responsibilities to a statistical model that tells them, for instance, who to hire, promote, or fire. To get these stakeholders on board, Guenole et al. (2017) provide four useful tips. First, a people analytics team must understand what issues line managers are facing and how analytics may help them tackle these issues. Second, why, how, and to what degree an analytical project may help line managers in their job must be explained well. Third, feedback should be gathered from line managers after the completion of an analytical project in order to learn how to improve. Fourth, past successful analytical projects should be presented to

line managers. It consequently appears that this group too requires a combination of education and product relevance to effectively make use of people analytics products.

Employees and employee representatives: The fourth main stakeholders of a people analytics team, namely, employees, are also affected by the insights and recommendations provided by a people analytics team (Green, 2017; Guenole et al., 2017). Therefore, it is argued that organizations should be fully aware of the legal and moral obligations they have to their employees and conduct research that provides value to the organization as well as to the employees (Green, 2017; Mondore et al., 2011). Guenole et al. (2017) add to this that especially projects with potential positive or negative effects for a certain group of people should be carefully thought through to avoid a situation in which a group of employees may be damaged or alienated. For instance, while an analysis may suggest that employees with certain demographical characteristics react less to a salary increase than others, it would likely cause issues if this group was the only one to be excluded from a salary increase. After all, the employees who were excluded might feel unfairly treated, and the employees who were included may feel unfairly favored.

Employees may also be a potential risk for a people analytics team, because they own their data and privacy is becoming increasingly important (Green, 2017; van den Heuvel & Bondarouk, 2017). As a result of the dependency on personnel data, Green (2017) warns that people analytics initiatives can be undermined if employees decide against sharing their data or provide irrelevant or untruthful data. To address this issue, Guenole et al. (2017) provide a number of recommendations. These are to be open with employees about how their data is being used, to ask for feedback about where additional analyses are needed, and to demonstrate the benefits that people analytics projects have for them. The authors argue that the latter may also result in an increased willingness of employees to share their data with the people analytics team in the future (Guenole et al., 2017). Thus, for a people analytics team to be effective in the long term, it appears that the relationship between employees and their representatives needs to be carefully managed by the team.

Other analytical teams: Rasmussen and Ulrich (2015) argue that collaborating with other analytical teams can be beneficial for sharing knowledge, analytical models, and techniques. They point out that this is especially beneficial to people analytics teams, considering that they are the newest type of analytical team and may thus lack expertise compared to the other analytical teams. Given that other analytics teams often also work with people data, there seems to be ample opportunity to benefit from their expertise indeed. This is also illustrated in one of the case studies described by Guenole et al. (2017) in which a people analytics lead believed that employees should be treated, and thus analyzed, in the same way as customers. He consequently applied customer segmentation to the workforce to determine what actions to take

for different employee groups in order to improve the employee experience. Another benefit of teaming up with other analytical teams is that people analytics can benefit from their data definitions and data (Rasmussen & Ulrich, 2015), which can also increase the credibility of the findings of a people analytics team (Guenole et al., 2017). By teaming up with financial analytics, for instance, a people analytics team can link profitability to employee survey data, which in turn can potentially help HR to make a stronger case for investing in new HR initiatives, as illustrated by the case study of van de Voorde, Paauwe, and van Veldhoven (2010).

The elements of a people analytics team's proper governance structure to safeguard compliance and achieve legitimacy

The main ingredient that a people analytics team requires for its analysis is data about its workforce. However, to protect people's privacy, a proper governance structure must be in place that is compliant with related legislation (such as the General Data Protection Regulation [GDPR] in Europe). Next, we focus on data governance (data management and ethics), governance of the people analytics function (organizational positioning, reporting structure, internal team structure, and delivery channels), and finally building and maintaining social legitimacy.

Data governance

In recent years, data governance has become more important than it was in the past (Guenole et al., 2017) due to the increased need to comply with data privacy legislation, such as the GDPR in Europe, and employees' increased concerns about privacy. As data governance involves all activities related to the management of data and the ethical questions that surround it (Davenport & Harris, 2017; Guenole et al., 2017), we discuss each of these topics below.

Data management: Proper data management is seen as a must-have capability of any people analytics team to keep the trust of employees and to comply with the law (van den Heuvel & Bondarouk, 2017; van der Togt & Rasmussen, 2017). Therefore, procedures and rules should be in place with regard to how data should be managed, maintained, and stored (Davenport & Harris, 2017). Aspects that should be considered by the team in this respect are anonymization, storage duration, storage location, data security, data access, data format, and data maintenance (Davenport & Harris, 2017; Guenole et al., 2017; Regulation(EU), 2016; Van der Laken, 2018). With regard to these topics, a people analytics team should be aware of the organization-specific agreements as well as the laws of the country in which it is operating (Guenole et al., 2017). In Europe for instance, many these elements are regulated by law (e.g. GDPR). As a consequence, laws are in place that state, for example, that personal data should not be stored longer than necessary (Regulation(EU), 2016) and that data should be

dealt with confidentially (i.e. accessed on a need-to-know basis) (Vegt, 2017). Due to the complexity of these topics, Guenole et al. (2017) recommend that a people analytics team should collaborate with specialized professionals, such as a data privacy officer. Professionals in this function have the task of ensuring that people's data is processed in compliance with the GDPR (European Data Protection Supervisor, no date), which is mandatory for any country operating in Europe. Therefore, to adhere to the law and be seen as legitimate, having the correct rules and procedures in place with regard to data management can be seen as another important pre-requisite for a team to work with people data and thus be effective.

Ethics: Guenole et al. (2017) define data ethics as the fundamental legal and moral principles about right and wrong related to the governance of data. Batistič and van der Laken (2019) argue that ethical considerations are even more important for an analytics team than adhering to legalization and privacy standards. They argue that this is especially the case when dealing with big data and predictive analytical models as they can, for instance, lead to self-fulfilling prophecies and bias (Batistič & van der Laken, 2019; Herschel & Miori, 2017), such as the aforementioned example in which gender discrimination was accidentally included in the selection algorithm. Van der Laken (2018) explains that the ethical side to people analytics is also important because simply adhering to the law may not always be sufficient. As an example, he argues that although employees in Europe are required to give consent for their employer to analyze their data, employees may not feel as though they have the choice to refuse. Being mindful of data ethics is also in line with the recommendation of Mackaluso (as cited in Guenole et al., 2017), who argues that even if an analysis is possible, it does not make it automatically right to do so. For instance, although analyzing health data might be tempting, it should be considered carefully if an employer truly wants to start steering employees towards "good" (e.g. healthy) behavior. Moreover, as it is unclear what "good" behavior is, this would grant employers much influence over an employee's life (Van der Laken, 2018). Therefore, Van der Laken (2018) recommends careful consideration of the purpose of an analytical project beforehand, and Guenole et al. (2017) suggest partnering with HR to ensure correct usage of the data. In summary, for stakeholders to see a people analytics team and its project as legitimate, and for the team's effectiveness, it is important that the team is seen as mindful of ethical concerns in addition to adhering to the law.

Governance of the people analytics function

Following the HR government and risk management kaleidoscope (Farndale, Paauwe, & Boselie, 2010), we believe that people analytics as a function should consider its structure, delivery channels, the governance and control of its products, and the monitoring of these products (Farndale et al., 2010) to safeguard compliance. In the next sections, we discuss the following internal governance ingredients: organizational

positioning, the reporting structure, the internal team structure of a people analytics team, and the delivery channels.

Organizational positioning: With regard to the organizational structure, two prevalent views are presented in the literature (Guenole et al., 2017). According to the first view, people analytics should be placed inside the HR function as a center of excellence (CoE). This center refers to a team that provides "leadership, best practices, research, support and training" on a certain topic, such as people analytics (Guenole et al., 2017:208). According to van den Heuvel and Bondarouk (2017), a possible benefit of placing people analytics within the CoE is that it may lead to a close collaboration with HR. This can be advantageous considering the previously mentioned importance of this stakeholder. In addition, Levenson (2005) argues that a CoE within HR is required because HRM-specific theoretical and statistical knowledge is required to add value through people analytics. The second view argues that a people analytics team would benefit more from being placed outside of HR and together with other analytical teams (e.g. Rasmussen & Ulrich, 2015). As previously mentioned, collaborating with other analytical teams is considered to be beneficial due to the possibility of sharing expertise, analytical models, and techniques and data. With regard to the latter, Rasmussen and Ulrich (2015) emphasize that only when personnel data is combined with data from other analytical fields, new insights will be born. As a result, the "so what" question, in which people analytics insights are translated to financial consequences (Levenson & Fink, 2017) and strategy (Minbaeva, 2018), may also become easier to answer. This is also what appears to be happening in practice as a number of people analytics practitioners have reported having a great impact on business issues while being part of the broader analytics department (Guenole et al., 2017).

Reporting structure: Although scholars do not agree on the best organizational positioning of a people analytics team, there is overall agreement about the importance of reporting to senior management. In particular, many scholars argue that a people analytics lead should directly report to the HR director (Smeyers 2016, as cited in Green, 2017; Guenole et al., 2017). According to Green (2017), this is crucial for three reasons. First, due to the HR director's unique position in an organization, he or she understands the organization's key people issues that the team can contribute to. Second, the HR director has the seniority to grant the team the required access to the right business leaders. Third, even in light of controversial analytical insights, the HR director has the influence to ensure that they are acted upon.

Internal team structure: As clarified in the section on the KSAO's of a people analytics team, an effective people analytics team has many different KSAOs. In practice, a people analytics lead's main responsibility is to effectively manage experts with different backgrounds and expertise, while also ensuring that the team and its

projects are successfully navigated throughout the business (Guenole et al., 2017). To do so successfully, that lead might choose to split his or her team into specialized sub-teams. Kaur and Fink (2017), for instance, reported that a little more than half of the companies they interviewed split their team into reporting and analytics teams. The reason for this decision is to protect the resources of analytical experts from the ever increasing demands for HR-related reports (Kaur & Fink, 2017). Moreover, while reporting and analytics could technically be placed in different parts of an organization, Kaur and Fink (2017) also found benefits to centralizing reporting and analytics in one team. For instance, analytics needs to have access to the data of reporting and also needs to be able to control the data reporting it is generating (Kaur & Fink, 2017). As mentioned before, reporting can also benefit from analytics by, for instance, reporting on KPIs that have a known link with organizational performance. Therefore, it appears that although creating sub-teams within a people analytics team can increase its overall added value, keeping these different sub-teams relatively close together within an organization is even more important to achieve effective coordination and collaboration.

Delivery channels: According to Paauwe (2004) and the HR government and risk management kaleidoscope (Farndale et al., 2010), a people analytics team should consider how and to whom the products of the team should be delivered. Apart from issues related to the management of stakeholders (see above), it should be noted that legal and ethical considerations should also be taken into account in terms of the delivery channel. The GDPR, for instance, states that organizations should process personal data with integrity and confidentiality, which generally means that people analytics teams are not allowed to deliver insights or data to stakeholders that will allow any individuals to be identified, unless the individuals consented to this beforehand (ICO, no date; Regulation(EU), 2016). This means that, practically, the team should consider, for instance, which demographics to report, the granularity of its reports, the sensitivity of the insights, and the purpose for which the data was collected. Moreover, this can also mean that after an engagement survey, some line managers in a team with high response should receive team insights, whereas a line manager with a team of only three respondents should not receive the same report due to the risk of personal identification. This will likely have consequences for the delivery structure and especially the capabilities of the IT and communication structure, which needs to be capable of reporting the insights on the correct level of granularity (i.e. team, department, business unit), while preserving the agreed upon anonymity.

Governance of external social legitimacy

The social legitimacy of an organization, and thus also a people analytics team, can be viewed through an internal lens (i.e. micro) as well as an external lens (i.e. macro). According to Paauwe and Farndale (2017:101), legitimacy is based on "relational

rationality," which ".....refers to establishing sustainable and trustworthy relationships with both internal and external stakeholders." As we have already mentioned how a people analytics team should approach internal stakeholders, in this section we focus on the external stakeholders the team requires to be perceived as legitimate. We specifically focus on 1) trade unions and employee representatives and 2) collaboration with external parties.

Unions and employee representatives. As unions and employee representatives aim to protect the rights and interests of employees, these stakeholders can be concerned about people analytics' usage of employee data. Especially in countries with a strong legislative basis for works councils, the agreement of a council may be required before a people analytics team is allowed to access and analyze certain data (Guenole et al., 2017). van den Heuvel and Bondarouk (2017) mention that only within a few "progressive" organizations, the people analytics team collaborates with unions and workers councils, which will benefit the social legitimacy of the team both internally and externally.

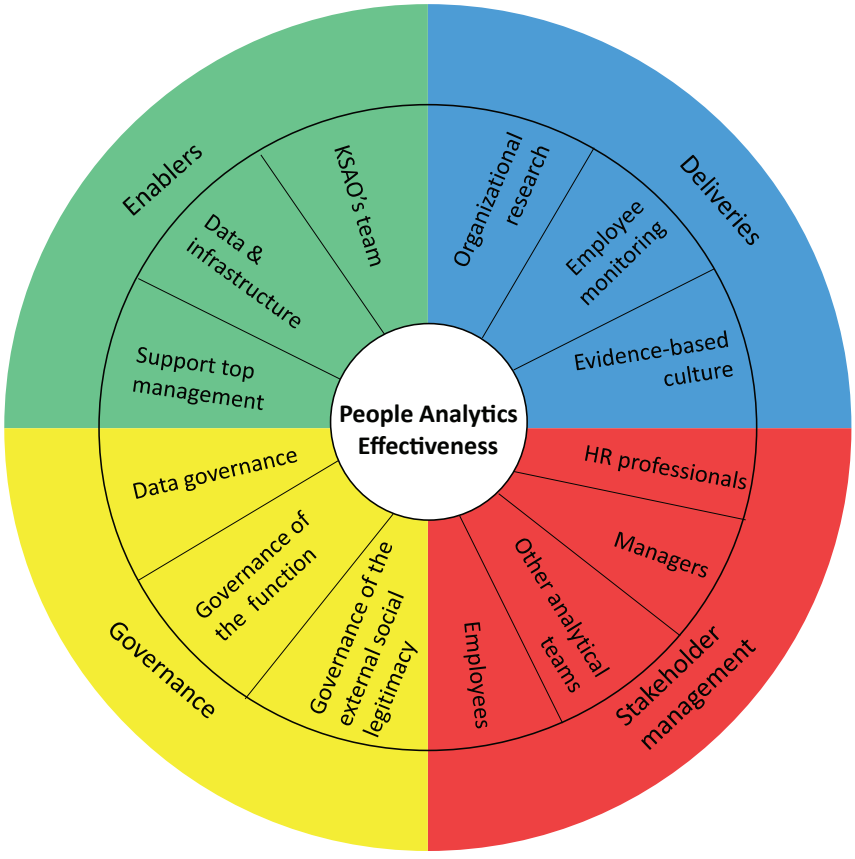
External parties: Various scholars suggest that teaming up with external parties, such as consultancy firms and universities (e.g. Angrave et al., 2016; Cascio & Boudreau, 2011), can be beneficial to a people analytics team and will add to its prestige and trustworthiness. The rationale for this is that consultants and academics can bring deep (behavioral analyst) expertise that can help take a people analytics team to the next level (Angrave et al., 2016; Levenson, 2005). By partnering up with externals,, companies may be able to showcase successful analytics projects to their stakeholders more quickly as a result and thereby accelerate the credibility of their analytics team (Guenole et al., 2017) and thus the social legitimacy of people analytics.

The People Analytics Effectiveness Wheel

Based on the previous overview, it is clear that there is not one ingredient that solely determines whether a people analytics team will be successful. Instead, multiple ingredients seem to be required to have the "enablers," "products," "stakeholders," or "governance structure" in place that will enhance decision-making and hence organizational performance. It also became clear that in addition to each ingredient contributing in its own unique way to the effectiveness of the team, a relationship also exists between the different ingredients and categories. For instance, while the internal governance structure of the team is important to achieve legitimacy, it will likely also affect where the team is based in the organization and hence the relationship with stakeholders. Based on the currently available literature, we can only state that the different ingredients are important for people analytics teams to be successful. However, we cannot yet determine what their relative importance is or what relationships among resources look like. As we believe that it is important to

provide practitioners in particular with a comprehensive overview of how to equip their people analytics teams for success, we bundled the ingredients under their specific category in a framework: the People Analytics Effectiveness Wheel (Figure 2.1). This framework provides an easy-to-grasp overview of the categories and the ingredients critical to these categories, as identified in this article. The benefit of the current representation is that it does not touch on the cause or consequence of the ingredients or relative relevance, as this is still in need of further exploration by future research.

Figure 1. People Analytics Effectiveness Wheel



Directions for future research

By reviewing the existing literature on (people) analytics, we managed to identify which enablers, products, stakeholders, and governance ingredients are critical for a people analytics team to be effective. Due to a lack of qualitative papers on the topic (Van der Laken, 2018), the most pressing question that remains is which processes should be in place to successfully transform these ingredients into increased organizational performance. Now that the People Analytics Effectiveness Wheel can be used as a guideline, the next step is to uncover these processes in empirical research. Therefore, our primary recommendation is to carry out case studies and/or other forms of qualitative research with people analytics among a range of companies with varying degrees of success and experience in order to capture the underlying processes between the different ingredients and categories of the framework. Furthermore, we recommend paying specific attention to the stakeholder and governance ingredients because we expect the most critical processes for a successful people analytics team to be present there. These ingredients will likely determine how internal and external stakeholders perceive a people analytics team, which will directly affect their willingness to take action on the analyses and insights the team delivers.

A second direction that future research could take is to study how the different ingredients may relate to and affect one another. For instance, while we believe that all ingredients are important for the success of a people analytics team, it may turn out that some ingredients are less critical than others. Moreover, we also believe that the ingredients may reinforce, substitute, or undermine one another's value in certain situations. In particular, we expect that the four categories may "reinforce" one another when they are highly developed, boosting the effectiveness of a people analytics team. In the case of "substitution," we imagine that a team that lacks deep psychological skills may bring in this knowledge by collaborating well with its HR stakeholders. Finally, with respect to "undermining," it may be, for instance, that teams in the initial stages of developing a strong data governance structure lack the data to build (predictive) statistical models. This in turn also lowers the value of highly advanced statistical skills within the team, making these skills less valuable. We consequently recommend that researchers investigate the way in which ingredients affect one another's effectiveness and whether primary or secondary ingredients for success can be identified.

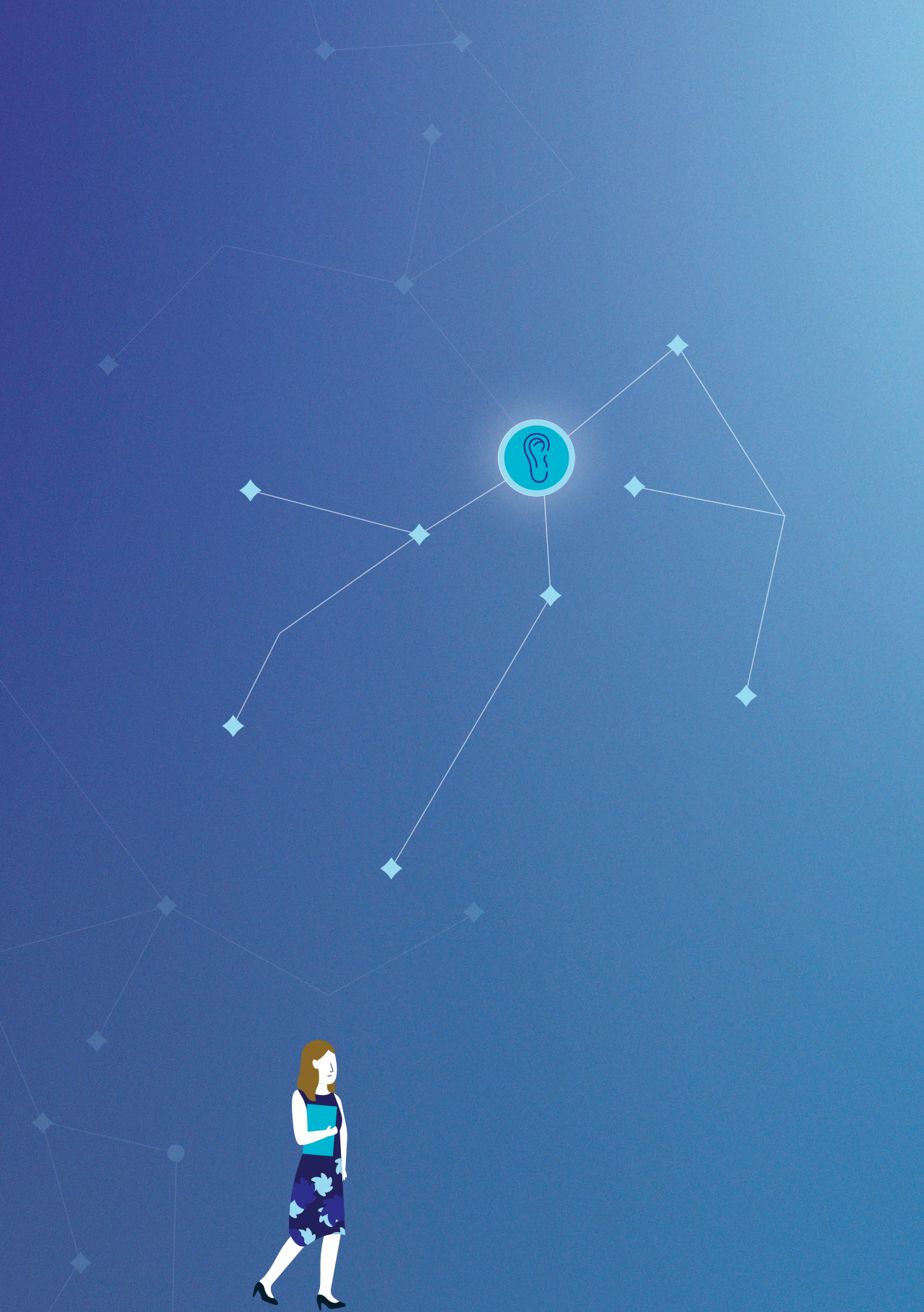
Third, although we believe that a people analytics team will be most effective when all of the different ingredients within the People Analytics Effectiveness Wheel are addressed accordingly, the inclusion of all the ingredients most likely requires a large number of (financial) resources and data, as well as a large analytics department. However, this is not to say that a small company will not benefit from conducting

people analytics as well. As research has primarily focused on large companies that are generally at the forefront of people analytics (e.g. Kaur & Fink, 2017), little is known about the success factors for people analytics in small and medium-sized firms thus far. We imagine they would use standardized analyses tools, join forces with similar companies, or conduct research projects in collaboration with academic scholars to reap the benefits of people analytics. To ensure that they are not left behind, we recommend future research to explore the way in which small and medium-sized organizations can execute people analytics effectively.

Conclusion

In this paper, we have identified and discussed the key ingredients that are required to establish an effective people analytics team based on the existing people analytics and business intelligence literature. This led to the development of our People Analytics Effectiveness Wheel, which can serve as an initial point of departure for enhancing decision-making and contributing with people analytics to organizational performance. From an academic point of view, our framework can be used as a heuristic device to explore the ingredients and processes that should be in place for a people analytics team to be successful. Exploratory follow-up research could also investigate how the different ingredients relate to one another and what their relative importance is. Furthermore, from a practitioner's point of view, our framework can act as a guideline for organizations that are considering how to set up their people analytics function. Finally, for organizations that already have a team, our framework can help them assess the different ingredients in terms of their quality, risk analysis, interrelationships, and areas for improvement in order to increase their effectiveness.

[1] Minbaeva, M. (ed) (2017) Human capital analytics: why aren't we there? [Special issue]. *Journal of Organizational Effectiveness: People and Performance,* 4 (2).



3

The road to people analytics effectiveness: A qualitative exploration of the inputs, processes, and outputs

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Abstract

Although people analytics has gained popularity, there is still a limited theoretical understanding of how an effective people analytics function might be created. Using the Input-Process-Output model as an organizing framework, we conducted 36 in-depth interviews with analytics experts and their stakeholders from nine multinationals to develop a heuristic framework on the inputs, processes, and outputs that a people analytics function requires to be effective. Our findings show that we can distinguish three types of inputs: license to operate (e.g. legislation), must haves (e.g. data), and nice to haves (e.g. organizational culture) and that these inputs relate to the function itself (e.g. skills of members), or are contextual factors (e.g. senior management support). Second, the processes required to transform input into outputs relate to the projects and stakeholders. Additionally, these stakeholders can be subdivided into four archetypes, skeptics, confused, enthusiasts, and strategists, and different tactics are needed to collaborate with each. Third, the function produces direct (e.g. advanced analytics) and indirect outputs (e.g. analytical capabilities of stakeholders) and to be effective, stakeholders have to use these outputs to make decisions. Finally, people analytics dynamically evolves and changes over time, so that the outputs influence the inputs and organizational context in the future.

Keywords: People Analytics, HR Analytics, Workforce Analytics, Talent Analytics, Qualitative Research

Introduction

The usage of data analytics in organizations, particularly in the human resource (HR) management function, has been a popular topic throughout the past years (Cheng & Hackett, 2019). Many organizations are consequently interested in establishing their own "people analytics" function (Deloitte-Insights, 2018). The purpose of this function is to analyze employee and workforce data to provide insights and recommendations to enhance business outcomes (Ferrar & Green, 2021). Practically, it may, for example, be used to identify prime hiring candidates (Feloni, 2017), predict employee turnover (Zhao, Hryniewicki, Cheng, Fu, & Zhu, 2018), and determine the effect of a work-life balance program on wellbeing (Edwards & Edwards, 2019). However, many organizations struggle with the effectiveness of their people analytics function (Boudreau & Cascio, 2017; Vargas, Yurova, Ruppel, Tworoger, & Greenwood, 2018). An effective people analytics function, enables stakeholders to take data-driven decisions (Garcia-Arroyo & Osca, 2019; Larsson & Edwards, 2021), supports the creation of an evidence based-culture (Ferrar & Green, 2021) and, through these, increases the demand for analytical insights (Vargas et al., 2018). Scholars have listed a myriad of causes that may explain the limited effectiveness of the function, such as the multidisciplinary nature of the work (McCartney et al., 2020), the unavailability of (high quality) data (Andersen, 2017), and the limited analytical capabilities of HR experts (Angrave et al., 2016; Fernandez & Gallardo-Gallardo, 2020; Rasmussen & Ulrich, 2015).

Although a growing amount of literature is available on people analytics effectiveness (Boudreau & Cascio, 2017; Cascio et al., 2019; Ellmer & Reichel, 2021; Guenole et al., 2017; Huselid & Minbaeva, 2019; Levenson & Fink, 2017), it remains largely unclear how organizations may establish an effective people analytics function (Fernandez & Gallardo-Gallardo, 2020; Qamar & Samad, 2021). This seems to be the case despite the various models that have recently appeared on the topic. Specifically, these models have all been developed based on literature reviews (i.e. Opatha, 2020; Peeters, Paauwe, & van de Voorde, 2020; Shet et al., 2021), single company case studies (i.e. Anger et al., 2021; L. Liu et al., 2020) or practitioner oriented research (Guenole et al., 2017). While none of these factors is problematic by default, it is an issue when there is a scarcity of empirical research available on the topic (Marler & Boudreau, 2017; Qamar & Samad, 2021). As a result, empirical research among multiple companies is needed to identify which elements contribute to the effectiveness of the people analytics function (Fernandez & Gallardo-Gallardo, 2020; Qamar & Samad, 2021).

More specifically, if we look at the currently available models it is striking that many different elements are identified as critical to achieving people analytics effectiveness. Some authors, for instance Shet et al. (2021), identify twenty-three elements in their

model, whereas others identify 'only' nine (e.g. Ferrar & Green, 2021). On top of this, there is also a large variation between the elements identified within these models. The elements included in these models, are for example, the Information Technology (IT) infrastructure required to conduct the analyses (i.e. Ferrar & Green, 2021; Peeters et al., 2020; Shet et al., 2021), the industry the organization operates in (Shet et al., 2021), and all in between. It is consequently important to identify the elements which are truly important and show how they are related. To do this, exploratory research among multiple companies is needed. For this reason, this paper will conduct in-depth interviews with members and stakeholders of nine different people analytics departments. This is our first contribution to the literature.

Second, it is important to examine the processes a people analytics function requires to transform its inputs (e.g. data) into the insights and recommendations stakeholders need to increase business outcomes (Peeters et al., 2020). Although the available models make note of different processes, these processes are not consistently present within all models. For instance, whereas various models make note of stakeholder management as an important process (e.g. Ferrar & Green, 2021; Shet et al., 2021), this is absent in other models (e.g. Guenole et al., 2017; L. Liu et al., 2020). It is consequently important to provide more clarity on the processes a people analytics function requires. As our exploratory research design will enable us to provide such clarity, this is the second contribution of this article to the literature.

Third, a people analytics function's insights and recommendations need to be used by stakeholders to make decisions (Ellmer & Reichel, 2021; Greasley & Thomas, 2020; van den Heuvel & Bondarouk, 2017). Without that, it is impossible to enhance business performance (Ellmer & Reichel, 2021). Nevertheless, stakeholders are rarely included within models on people analytics (with noticeable exceptions of Ferrar & Green, 2021; Peeters et al., 2020; Shet et al., 2021). Furthermore, to the best of our knowledge, none of the existing models has been developed using data from stakeholders. Considering their critical role for the people analytics function, we also interview stakeholders alongside members of the people analytics function. This is our final contribution to the literature.

Based upon the previous, this study will establish an empirically grounded framework on the elements a people analytics function requires to be effective. This framework can be used by other scholars to guide empirical enquiry and is an intermediary step towards hypothesis building (Bourgeois, 1979). Furthermore, as the exploration of the processes the function requires is one of our primary goals, we use the Input-Process-Output (IPO) model by Kozlowski, Gully, Nason, and Smith (1999) as an organizing framework. This is similar to the approach taken by Margherita (2021) in his literature review on people analytics.

This research also has a number of practical contributions. First, as described earlier, many organizations are currently struggling to use people analytics effectively (Ledet et al., 2020; Orgvue, 2019; Vargas et al., 2018). By expanding our theoretical understanding on people analytics, our paper aims to equip organizations with the knowledge to execute people analytics successfully. Second, by researching the collaboration processes with stakeholders in more detail, our paper offers insight into how stakeholders can successfully be involved in people analytics projects (van den Heuvel & Bondarouk, 2017). This should not only further increase the effectiveness of the people analytics function, but also enhance the quality of the decisions made by HR managers and (senior) managers regarding the workforce (Rasmussen & Ulrich, 2015).

Existing frameworks on people analytics

Within the literature, there various models are available that identify the elements a people analytics function requires to be effective, such as the "nine dimensions for excellence in people analytics" from Ferrar and Green (2021), the "workforce analytics operating model" from Guenole et al. (2017), "people analytics effectiveness wheel" from Peeters et al. (2020) and the "framework for adoption of data analytics in HRM" from Shet et al. (2021). Although there are other models available too (e.g. Anger et al., 2021; L. Liu et al., 2020; Opatha, 2020), we will focus on these four as they seem most complete and target the people analytics function instead of a single project. We discuss each of these briefly. First, as the name implies the "nine dimensions for excellence in people analytics" model identifies nine dimensions crucial to a people analytics function. These relate to the foundation of the team (e.g. governance, culture), the resources it has at its disposal and the value it brings (Ferrar & Green, 2021). Second, the "workforce analytics operating model" describes the strategy, governance structure, the implementation (e.g. project management, team structure) and the accountability (e.g. prove of its success) required for success (Guenole et al., 2017). Third, "the people analytics effectiveness wheel" describes the enablers, stakeholders, outputs, and governance structure required for a people analytics function to be effective (Peeters et al., 2020). Fourth, the "framework for adoption of data analytics in HRM" is the most exhaustive model in terms of the number of elements it addresses. This model demonstrates the technical, organizational, environmental, data governance and individual factors a people analytics function requires (Shet et al., 2021).

While each of these models provide guidance on how a successful people analytics function can be established, they all seem to provide a piece of the puzzle. What is more, there are only two things that all four models have in common. These are, that they all identify "data" as an important element and none of them include any relationships between the elements they have identified. For each of the models, we will now discuss a number of limitations. First, the "nine dimensions for people analytics

excellence model" pays little attention to the role of ethics. This is unfortunate, as people analytics needs to have sufficient ethical standards in place to protect the interest of the employees and the reputation of the organization (Giermindl et al., 2021; Tursunbayeva et al., 2021). Second, "the workforce analytics operating model" is relatively inward focused. Whereas other models identify elements, such as the organizational culture (Shet et al., 2021), stakeholder management (Ferrar & Green, 2021) and top management support (Peeters et al., 2020) these are not discussed within the "operating model" of Guenole et al. (2017). Third, "the people analytics effectiveness wheel" discusses the inputs and outputs of a people analytics team (Peeters et al., 2020). However, it does not describe what takes place in between (e.g. processes) and pays little attention to contextual factors (e.g. the culture within the organizations). This is problematic, as prior research identified both as relevant factors (Ellmer & Reichel, 2021). Fourth, from all the models we discussed, the "Framework for adaption of data analytics in HRM" is the only model that explicitly focuses on the HRM function. This is controversial, as other stakeholders can also benefit from people analytics when they take people-related decisions (Ferrar & Green, 2021). All in all, we believe that none of the existing theoretical frameworks on people analytics provides the sufficient complexity and depth required to understand how people analytics effectiveness can be achieved.

Using the IPO model to explore the inputs, processes, and outputs of a people analytics function

Within the literature, the IPO model by Kozlowski et al. (1999), seems to be the most suitable model to help us develop a heuristic framework for the effectiveness of people analytics function (Margherita, 2021). The IPO model is a relatively abstract model that distinguishes inputs, processes and outputs. As a consequence, many of the aforementioned theoretical models on people analytics can, in some way, be mapped to the IPO-model. We describe in the remainder of this paragraph how the elements identified by these other models can be mapped to the inputs, processes and outputs of the IPO-model. First, in the context of a people analytics function, inputs refer to factors that enable and constrain the people analytics function. Within the existing models, these are, for example, senior management support, data and competencies of people analytics experts (Guenole et al., 2017; Peeters et al., 2020; Shet et al., 2021). Second, based upon these inputs, outputs can be produced that provide insights and recommendations to stakeholders (Ferrar & Green, 2021). These may be, for example, predictive models on employee turn-over (Gaur, Shukla, & Verma, 2019) and scorecards on headcount (Cascio & Boudreau, 2011; Guenole et al., 2017). Third, the IPO-model recognizes there are certain processes required to transform these inputs into outputs. Although there is a lack of research on the processes (Peeters et al., 2020), most models distinguish processes related to specific people analytics projects (e.g. prioritization of projects) and stakeholders (Ferrar & Green, 2021; Guenole et al., 2017; Shet et al., 2021). Practically, the attitude of stakeholders

towards people analytics (Vargas et al., 2018), can for example, determine whether insights will be translated into actions (Cascio et al., 2019). In sum, we believe that by using the IPO-model as a guiding framework, we will be able to build on the models that have been developed for people analytics in the past, while also exploring the inputs, processes and outputs underlying the possible effectiveness of the function through in-depth interviews. Consequently, it can thus be used as our basis for a heuristic framework on people analytics.

Research design

For this study, we used in-depth interviews to explore which inputs, processes, and outputs are crucial for people analytics effectiveness. Considering most organizations have not yet advanced beyond descriptive analytics, such as headcount analyses and organizational charts (Orgvue, 2019), we used the purposive sampling technique (Etikan, Musa, & Alkassim, 2016). Specifically, only organizations known in the field for their advanced analytics achievements were approached, as they would likely have the richest experience with all (analytical) aspects of using people analytics to provide insights and recommendations to increase business outcomes. First, organizations with a reputation regarding people analytics were identified in collaboration with a number of experts in the field from our personal networks. Second, organizations were selected to ensure that there was maximum variation in the sector and country in which these organizations operated. This enabled us to study people analytics from various angles (Etikan et al., 2016). In total, we selected 19 different companies operating in various sectors and countries (primarily European- and USA-based businesses). Third, in line with the case study method (Ritchie & Lewis, 2012), we requested that each organization participate with multiple members from within and outside the people analytics function in order to gain a thorough understanding of how people analytics effectiveness can lead to data-driven decision-making and impact within the different companies. In particular, we requested in-depth interviews with key members of the function, the people analytics lead (PAL), a data analyst or scientist (DA), and a consultant or translator (TL), as well as their key stakeholders. These were a (senior) HR leader (HR), a line manager (M), and a legal or risk officer (DPO) from outside the function. The roles were chosen based on their assumed familiarity with people analytics (Guenole et al., 2017) and their presumed accessibility (e.g. top management was excluded from the sample based on these grounds). Fourth, talks with potentially interested organizations followed (N = 19) in which we explained the research in more detail. In total, nine different organizations agreed to participate (53%), which resulted in 36 in-depth interviews (four on average per company) between March 2019 and September 2019. Although most interviews were completed on-site, others took place via Skype due to the location and availability of the interviewee. The interviews took between 45 and 90 minutes and were transcribed verbatim. Table 3.1 lists the roles/functions for each

company that were interviewed; these roles sometimes diverged from our initial research set-up due to specific organizational circumstances (e.g. line management being insufficiently involved in people analytics).

For each interview, a topic guide (see appendices) was used to ensure that roughly the same topics were covered for each interview, while also allowing sufficient leeway to diverge and expand the topic guide when needed (Ritchie & Lewis, 2012). The topics were derived from the aforementioned models. Commonly asked questions were, for example, "What kind of inputs does people analytics need in your opinion?" (input), "What kind of products does people analytics (deliver to you)?" (output), and "Could you describe what your collaboration with [people analytics experts / the primary stakeholder] looks like?" (process).

Analysis

The transcripts were analyzed using Atlas Ti version 8. We followed the guidelines described by Ritchie and Lewis (2012). In the first stage, the first author, who also conducted the interviews, further familiarized herself with the data by reading six (16%) of the transcripts in depth. For each of the interviews, emergent themes were written down. This resulted in a list of 329 themes (including doubles). We sequentially discussed these themes and decided on an initial coding scheme of 102 codes. As all codes thus emerged from the data, this method helped us to reduce the influence of our own biases on our coding scheme. In the third phase, we applied our coding scheme to all 36 transcripts and further refined it through an iterative process. This implies that we added codes that we initially missed, refined existing codes (e.g. split into multiple codes or relabeled) and repeatedly revisited transcripts as our coding scheme evolved. Furthermore, we decided to create specific codes for the interviewees working for the people analytics domain and for their stakeholders, so that we could see the differences between these two groups more easily. After the initial coding was complete, to answer the research question, we discussed the emergent coding scheme and the appropriateness of the codes. This resulted in a final coding scheme of 248 codes at the end of Step 4. During the fifth step, we discussed the codes and decided on the second-order constructs that emerged from the data. In the end, we settled on 25 labels, such as "data," "senior management support," and "analytical capability." In the final step, we matched the second-order constructs to the categories of the IPO model, meaning inputs, processes, and outputs. To protect the identity of the interviewees, we refer to them using codes that relate to their function.

Table 3.1. Overview of the interviewees per company

	People Analytics Lead	People Analytics\ sub-leads	Data analyst / scientist	Consultant / translator	Operational manager	Senior HR manager	Legal / risk expert	Total
Financial services	1		1	1		1		4
Conglomerate	1		1*	1*		1		3
Travel agency	1	3	1		1	1	1	8
Pharma	1		1	1		1	1	5
Tech	1							1
Professional services	1		1	1		1		4
Consumer goods	1							1
Financial services	1		1	1	1	1		5
Oil and gas	1		1*	1*	1	1	1	5
Total	9	3	7*	6*	3	7	3	36

* In certain companies the translator/consultant and data scientist/analyst were combined roles, which means that one interview was conducted with the person covering both roles.

Empirical findings

Following the IPO model as a guideline, in the next sections, we discuss the inputs, processes, and outputs that we found within our interviews.

Inputs of the people analytics function

Based on the interviews, we found that the KSAOs of people analytics experts, the data, the IT infrastructure, legislation, the set-up and hierarchical positioning of the function, and the organizational culture were important inputs (see table 3.2 for illustrative quotes).

KSAOs: The interviewees listed over 20 different KSAOs as relevant for people analytics experts (see Table 3.3). In line with the literature, they mentioned all six competencies displayed in McCartney et al. (2020) competency model. Out of all of these, technical knowledge was mentioned most frequently, following by consultancy and communication skills. Furthermore, interviewees mentioned that a combination of skills was often required, as experts with strong statistical skills, for example, also needed to be able to explain the results in plain language in order to be effective.

Interestingly, respondents also made a case for KSAOs that have rarely been mentioned in the literature thus far. First, they argued that legal knowledge helped to govern the data in the right way and in the conversations with legal experts. Second, it was believed that anyone become a people analytics expert, regardless of their educational background, as long as they were interested in working with people-related data, were curious, were creative in their problem solving, and had a sound ethical compass. In conclusion, an effective people analytics function appeared to require a high number of KSAOs. This makes the function a unique environment in which to operate, as PAL4 described: *"One of my favorite things about people analytics is, more so than most other domains I've seen in my life, we really need eh, inter-disciplinary approaches."*

Table 3.2. Illustrative quotes of the inputs of a people analytics function

Input type	Example
KSAOs	*"So it means statistics, mathematics, coding skills. You don't need to be the genius, you don't need to be the person who knows latest and greatest. But you should to be really good at knowing the basics of... let's take statistics for example. Being able to explain it to like a group of kids that just walk [by] right now. To explain what you are doing. That to me is that... if you don't know how... don't know that, it's very difficult to be successful in the business"* (PAL1). *"We've also had folks who were doing strategic workforce planning. Eh, we've had great success with people who had supply chain in their background. Really understand how to eh, manage a flow of resources, through a system. To ensure that the right resources are in the right place at the right time"* (PAL4). – how diversity in educational backgrounds can benefit people analytics teams.
Data	*"Right now, we're having a meeting that's planned in August to tell to some of the more senior people, to tell them that there is really a business need for us to have salary data. They are very hesitant to give us that, for one erm, the global data erm, privacy issues that are you know, concerned, they don't, yeah, that's one issue"* (DA6). *"I think our team is quite good eh, to say, 'no we cannot do it'. Because we recognize what our limitations are for that potential study. So, we say, 'okay, we just don't want to recommend something that we are not comfortable with'. Because again, we don't have enough data. Or, we just need more data. Eh, more data points to validate something. (....) Data quality. Ehm. We are aware of some data that they are not happy with it. Ehm. For example, absent days is not very well. So, we don't run any projects on absent days. Yet"* (DA3).
IT infrastructure	*"I would say you need all HR-data from all domains of the organization into one system. Currently, it is fragmented for us, which works against us. It causes us to be slow, needing to follow all kind of procedures and that... because of that we can make too little impact"* (TL3). *"We always want more data, always want more access to more data in a more structured way. So, it's something we will always push for more of, and we are in the process – as many, many companies are – of moving on to a data lake platform. But we are finding that very costly and very time consuming. But again, I don't think we're unique (...) I think investing in data infrastructure, so it doesn't yet bring additional benefit, is quite a difficult thing to ask the business to pay for it as obviously the return on investment is hard"* (PAL9).

Table 3.2. Illustrative quotes of the inputs of a people analytics function (continued)

Input type	Example
Legalisation	*"So, we didn't have a, we didn't have a privacy organization, really. (...) So, that's when the privacy operating model at X [company name] really got a lot bigger"* (DPO1). *"And in Europe with GDPR being in the picture we have to be extra cautious when dealing with individual level data"* (DA2).
Set-up	*"So, basically if some stakeholder comes to you [advanced analytics team] with a question, that you can't answer eh, with immediately, or with the current data. Then they [the survey team] develop a survey for you. You analyze it and you feed it back to them"* (DA5). *"Reporting has very different pressures. Far more voluminous. You're serving different stakeholder groups, usually. Ehm. And you're working with different kinds of technology. Ehm. And in many cases, it's a kind of ongoing business as usual kind of requirement. Ehm. Monthly reports, quarterly, annually. As well as ad hoc. Ehm. Analytics on the other hand, is project based. Ehm. It's about solving a problem. But it's bigger than that. It's about actually getting to the root of it. Helping people to understand the project analytics, in its minute nuance. And then, actually looking for the people related factors that are going to help solve it. So. So, they are very different disciplines. Ehm. It's important to allow them to be different disciplines. I think, having a team that tries to do both, allows noise, allows confusion"* (PAL2).
Hierarchical positioning	*"And they [business stakeholders] are like: 'your people [department], but you're not people [department], but you're the analytics team right?' So it's almost like we have got a little bit of... for a lack of a better word: street credibility, right? With our peers. Cause you're not the people department really, although you kind of are. You're organizationally located there, but you kind of speak our language. Or you are not really 'them'"* (PAL10). *"I think that [hierarchically being placed in the business analytics function] also helps us get a broader reach into the organisation in terms of the business understanding what we can do and the potential value we can create from people analytics and also access to a broader range of problems and yeah, resources"* (PAL6).

Table 3.2. Illustrative quotes of the inputs of a people analytics function (continued)

Input type	Example
Organizational culture	*"Because you know, data privacy is also a major ehm, eh I don't know how big to make it. It's both of value, major priority. Ehm. We spend a lot of our time making sure we are incredibly sensitive to data pr... we are, we are, I am personally very ehm, overboard with making sure there is never a news item that ever comes out. You know, that embarrasses us. So, if anything, actually, I have very senior leaders right now, yelling at me. Because I won't allow them to print an analysis that I've put out"* (PAL5). *"Let's not forget, X [company name] is a tech company, and has been an online company which means data is everything. So, we don't need to argue about servers and stuff"* (PAL1).
Support management	*"We had, we had the luck that er, our er, former er, HR er, Ja, was keen on, on, analytics and had a good standing within the er, board so she could provide us enough budget to implement those tools so really we started to implement the Business Warehouse er, and based on that er, we, we built er, new tools"* (DA4). *"I think where they [the people analytics function] sit in the organization. They report in to a very senior person. So, I think, they ehm, yeah. I think indeed they are very well positioned. I think it's got X [department name]. So, it's a highly visible part of the organization. Ehm. So, yes. I do think it's helped their, their visibility"* (M2). *"I mean, I happen to know X [name of the leader]. Because I worked with him years and years ago. When he was in a completely different role. Ehm, so I feel very fortunate. Because when I have a question, I can go to him. And he'll let me know who's working on what"* (HR5).

Table 3.3. The KSAOs of a people analytics function

Technical skills	Soft skills	Content skills	Personality traits
Statistical skills*	Consultancy skills*	Business knowledge*	Creativity
Data management skills*	Storytelling skills*	HR/Psychological knowledge	Curiosity
Information technology skills	Communication skills*	Research knowledge*	Innovator
	Project management skills	Legal knowledge	Learner
	Relation management skills		Interest for (people) data*
	Visualization skills		Analytical mindset
	Management skills		Pragmatism
	Change management skills		Ethical compass*

Note: Generally, the KSAO's with a * appeared to be must haves, whereas the others were considered nice to have.

Data: The function depends on the availability, accessibility, quantity, and quality of the data to run analyses. First, in terms of availability, the function struggled with the fact that certain data was not gathered within the organization (e.g. exit surveys) or that historical data was disrupted by other initiatives (e.g. the implementation of a new performance management system). Second, with regard to accessibility, people analytics could face challenges obtaining permission to access the data due to its sensitive nature (e.g. salary or health data), technical challenges (e.g. data being stored in multiple locations and formats), or legal challenges (e.g. no permission to ask about nationality or gender). Third, it could also struggle with the quantity of the data. However, as all organizations included in this research were large multinationals, this only appeared to be an issue when conducting analyses for a small subset of a company. Fourth, most organizations faced problems regarding the data quality. This issue could, for instance, be caused by the data being manually inputted by many people or by having unclear data definitions or incorrect data (e.g. people not answering a survey truthfully). Based on the interviews, it appeared that people analytics functions struggled most with data quality and accessibility and were therefore limited in the types of analyses they could perform.

IT infrastructure: Interviewees deemed a sound IT infrastructure to be critical in order to do their jobs. However, many interviewees expressed negative views about the existing infrastructure, describing it as *"counter-productive"* (PAL2) and an *"impediment"* (PAL5). All organizations included in this research were consequently working to improve their IT infrastructure in some way. Specifically, they implemented systems that stored all HR data into one HR information system and moved all their data (incl. non-HR data) into warehouses and data lakes. Although people analytics experts were involved in this process, the implementation of the IT infrastructure was described as a long and time-consuming process, which involved many (third) parties.

Legislation: Legislation, such as the General Data Privacy Regulation (GDPR) that has come into effect in Europe, appeared to be an important input for people analytics. While some interviewees said that only small adjustments were required in their organizations to ensure compliance, others stated that it was a significant change. Another aspect of legislation that was found to be a struggle was complying with local legislation on top of widespread legislation such as the GDPR. Some organizations therefore preferred to solve local people analytics questions (i.e. coming from one country) locally within the country.

Set-up*:* Based on the interviews, it appeared that a people analytics function could be set up in many ways. Some organizations included in this research only had of a small core team that could be extended with, for example, data scientists from the general analytics domain or externals when required. Others established one large department that included related areas, such as the data management. The size of

the people analytics functions included in this research hence varied between four and 70 members. Noticeable was that all organizations, regardless of the size of their people analytics function, struggled to meet the high demands for people analytics insights from stakeholders. As a result, all organizations were rapidly expanding their people analytics function.

As people analytics functions grew, sub-teams were often established. Most of these sub-teams focused on specific outputs, such as reporting, advanced (modeling) analytics, surveys, research, and data management, but others were centered around specific HR domains, such as recruitment. One of the most important benefits of these sub-teams was that each (product) has its own challenges. However, interviewees also warned that stakeholders may get confused about which team delivered what. Since the different sub-teams were able to support one another, the general recommendation was to have all sub-teams report to one leader who oversees them all.

Hierarchical positioning: The hierarchical position of people analytics was largely dependent on its place within the organization in terms of the functional line and reporting hierarchy. With regard to the former, while most were part of the HR function, people analytics could also be placed outside of HR. Being placed in HR appeared to have two benefits: first, people analytics experts could easily interact with (one of) their main stakeholders and second, the analytical capabilities of HR experts could be improved during these interactions. Two important downsides were also mentioned. First, some organizations expected people analytics to solely focus on HR issues, which meant it was challenging to contribute to the overall business strategy and to have a financial impact. Second, due to the reputation of HR with data and analytics, business stakeholders could be skeptical towards people analytics. Being placed within HR could thus be both beneficial and a drawback.

With regard to the reporting hierarchy, most people analytics leaders reported to the chief HR officer (CHRO) or one level below the CHRO. The function's hierarchical position affected it in three ways. First, it affected the visibility of the function and the signals sent to stakeholders about the importance of data-driven insights. Second, it affected the opportunity to educate senior stakeholders; for example, people analytics leaders who joined senior management meetings could explain how people analytics could be used to tackle management's problems. Third, it affected the function's insight into what strategically relevant projects were. This, in turn, was highly relevant for the effectiveness of people analytics functions.

Organizational culture: The organizational culture affected the people analytics function in two important ways. First, organizations with a natural affinity for analytics (such as tech companies) received more easily approval from senior management for

the large (IT) investments they required compared to functions operating in other organizations. Furthermore, as the people working within these organizations had a greater affinity for analytics – being, for example, scientists, IT experts, or financial specialists themselves – there was also more interest from stakeholders within the business to collaborate with people analytics experts. Second, the organizational culture also affected both the risk appetite within the organizations and the number of approvals required to launch a people analytics project on top of the legal requirements. Some interviewees mentioned that their organization was highly risk averse and had many protocols and approvals in place on top of the legislation requirements. While some interviewees believed that their organization was laying down too much red tape, they also recognized the importance of complying with the law and avoiding negative publicity.

Senior management support: Finally, the support that people analytics functions received from senior management appeared to be a critical input for three reasons. First, as senior management is responsible for key decisions within an organization, it decides where resources are allocated. For people analytics functions, this meant that management's support determined their investment opportunities in, for example, new members and IT tooling. That support also meant that sufficient political power and resources were available to act on the insights provided by people analytics. Second, senior management could also help people analytics experts in their interactions with other stakeholders by emphasizing the value of people analytics, role modeling, and providing hands-on support. With regard to the latter, a member of the senior management team, for example, intervened when a data owner initially denied the function access to a certain dataset. Finally, senior management support also determined where the function was placed within the organization and how much exposure it received as a result.

The ways in which people analytics achieved the support of senior manager differed. In most cases, senior managers were supportive due to their educational background, their previous working experience, success stories (of other companies), or a fear of missing out, or through the influence of the people analytics leader. On the one hand, the latter was established through the personal network of the leader, who may, for instance, have worked with the senior managers in that network in the past. On the other hand, it was also affected by the leader's ability to pick up relevant projects from senior management in a timely manner. Finally, the interviewees frequently mentioned that their company hired senior managers with an affinity for data. As a result, the people analytics function also acquired additional support without taking action.

Processes

Eight processes emerged from the data that transformed inputs into outputs. The processes could be subdivided into two categories: project- and stakeholder-related

processes. First, for project-related processes, the way in which people analytics functions prioritized, managed, and executed them appeared to be important. Second, with regard to the stakeholders, the attitudes of both parties, the collaboration process, and partnerships appeared to be important.

Project selection: People analytics experts created project proposals themselves or received project requests from their (senior) stakeholders. These project requests were often submitted informally to the people analytics leader, as a senior manager explained: *"I'd call back for X [name of the people analytics leader] and say, um, 'I'm concerned about what's happening in this business area (...) can you help me?'"* (HR4). This means that the *hierarchical positioning* of the function is critical. If people analytics experts come up with a project themselves, then their own *KSAOs* and *data* available within the organization are more relevant inputs. People analytics functions generally selected their projects based on four criteria: the complexity, impact, sponsorship, and resources required to execute a project. First, the complexity of a project was assessed by reviewing whether sufficient (high-quality) *data* was available. Furthermore, the difficulty to acquire that data was determined (*IT infrastructure)*, the level of sensitivity of the topic (e.g. diversity and inclusion), and the *KSAOs* required to execute the project. Second, the expected impact of the project was assessed by reviewing its alignment with the (HR) strategy and the scalability of the output to other areas within the business. Third, it was verified whether sufficient *senior management support* was available for the potential output in order to guarantee that actions could be taken based on the insights. Fourth, some functions performed a resource assessment before taking on a project. Since people analytics typically received a multitude of project requests, selecting the right project was seen as an important and challenging process, as PAL9 explained: "*We have to prioritize and we have to – I think one of those most difficult things to do is understand how much time something is gonna take.*"

Project execution: After selecting a project, people analytics experts would work on its execution. Generally speaking, projects appeared to be executed in eight different stages, and the *KSAOs* of people analytics experts were relevant for all stages. First, the research scope of the project was determined, often with a *senior management stakeholder*. Second, the required *data* needed to execute the project was identified. Third, the research method to adequately answer the question was decided on using primarily their *KSAOs*. Fourth, people analytic experts gathered the *data* using the *IT infrastructure*. Fifth, the *data* was analyzed predominantly using the *KSAOs* of these people analytics experts. Sixth, they interpreted and presented the results mainly through their *KSAOs*. In the seventh stage, it would be up to the stakeholder to take action based on the findings provided by the people analytics experts. For this, *senior management support* was crucial as management generally determined whether action was indeed taken. Moreover, in contrast to subject matter experts,

such as HR professionals, management could also be more willing to take action on insights that are in contrast to its initial assumptions, as DA5 explained: *"Mostly the people who are the sponsors [= involved senior managers] (...) they, well, they see the bigger picture, right. When they have the motivation of the bigger picture. It's much easier to eh, accept evidence that contradicts their beliefs."* Eighth, people analytics checked whether the actions had the desired effects. Although desired, the latter was not often done in practice for two reasons. On the one hand, the number of actual actions taken by stakeholders appeared to be limited. On the other hand, people analytics functions were generally still struggling to get the other phases right and thus prioritized improving the first seven project execution phases first.

Finally, it should be noted that although these eight steps may appear to be a linear process, people analytics projects went back and forth between these project stages when needed. For example, if the stakeholder was not satisfied with the initial results or the *data* appeared to be unavailable, it could be required to go back in the process and re-scope the project.

Project management: Project management is another important process in transforming inputs into outputs. In this regard, there are two sub-processes to consider: the way the people analytics experts manage projects internally and the management of the involved stakeholders. With regard to the former, the *set-up* and *KSAOs* of people analytics function appeared to be important inputs. For example, functions that consisted of multiple sub-teams often assigned projects based on their expertise (e.g. reporting requests to the "reporting team"). Another common method was to distribute the tasks in line with the *KSAOs* of the members. In this case, a "consultant" (i.e. a role within the people analytics function), for instance, scoped a project, while a data analyst completed the analysis. Although some interviewees were in favor of distributing tasks in line with people's *KSAOs*, others believed it was better to have the same person(s) constantly involved in a project for the sake of the project's continuity and clarity for stakeholders.

Furthermore, with regard to stakeholder management, the (expected) outcome, follow-up, and connection to management's needs were emphasized. First, interviewees argued that stakeholders needed to be clear about when and what they could expect from the output. This is, according to TL4, an important task for the "consultants" within the function to ensure a mutual understanding between other people analytics experts and their stakeholders: "*They [consultants] have to manage the stakeholders in a manner that the stakeholders understand. That, this isn't the only project. Is then after them. They have limited resources to deliver on somewhat unlimited demand.*" Second, various interviewees recommended ensuring that stakeholders are aware of the need to take follow-up actions based on the insights provided by people analytics. This was required because some interviewees

mentioned that they (had) struggled with stakeholders not following up their analyses with actions or ignoring their output altogether (i.e. *"Others ehm, have not really acted upon that. Because they were not very convinced of the results"* [PAL7]). Third, it was recommended to connect with the needs of the stakeholders to ensure their commitment. This helped people analytics functions to deliver the output the stakeholders required and ensured that stakeholders would follow up with actions.

Compliant and ethical behavior: For the legitimacy and acceptance of the outcome of any people analytics project, it was important that the project was compliant with the law and ethically justified. The compliant and ethical behavior of the people analytics function appeared to be largely determined by the *legislation*, *organizational culture*, and *IT infrastructure*. The IT infrastructure, for instance, could determine what information people analytics experts had access to by default. This meant they have to take action to process additional data if this is required to answer a specific question. Within this space, people analytics functions typically employed three processes to be compliant and ethical. First, they had various processes in place; these were, among others, data management policies (often related to organizational policies and legislation) and assessments. Assessments could be related to, for example, privacy, risk, or ethics and had to be completed for each project separately. Second, the attitude *(KSAOs)* of people analytics experts affected their compliant and ethical behavior during a project. On the one hand, people analytics experts argued that the price for breaking the law was high (e.g. reputational damage for the company, the loss of their job). On the other hand, they also saw compliant and ethical behavior as critical to enhance and maintain the trust of their employees. Various interviewees consequently argued that the people analytics function should go beyond what is legally required and evaluate a project through an ethical lens as well. This could be done, for example, through an ethical assessment, as PAL2 described: *"So, we have some framing questions (...) what they do, they get you thinking about the topic in a critical manner. And then, there are some ehm, questions below that, which we score. And if those scores don't ehm, don't match what we think is acceptable. Then we go back, and we won't do it."* While all interviewees believed in the importance of compliancy, some of them, such as TL3, also felt that the procedures were bureaucratic and time consuming: *"The checks and balances are in essence good, only the manner which, I believe, the company implements it is just very bureaucratic and slow."*

Third, collaboration with legal partners or DPOs appeared to be another important process that affected the compliant and ethical behavior of the function. On one side of the spectrum, some of the functions worked closely with these experts to ensure that the latter were in the know about all the projects from the initial stages. This helped people analytics to consider a number of compliancy and ethical issues from the outset. On the other side of the spectrum, some functions appeared to reach out

to these experts only whenever a project required their approval. While the people analytics would generally gain the required approval, this seemed to take longer than for functions who worked closely with the legal experts right from the start. In the collaboration process with the legal experts, tension between the interests of the legal expert and those of people analytics was typical. This tension and collaboration was explained by DPO1: *"Our [legal] whole kind of privacy philosophy is to absolutely use the least amount of information required for the purpose that you need it. Ehm. Which – in a world that is digital data driven, analytics driven – and the mantra is more data is better. (...) Rather than just telling the business, no, no, no. Sometimes we have to stop things. But more often than not, we can find a way to make it compliant."*

Stakeholder types: It emerged that people analytics functions considered senior HR leaders, senior business leaders, and top management to be their most important (internal) stakeholders to whom to deliver outputs. Although some functions served line managers too, these were exceptions. Next to these customers, people analytics collaborated with various experts, such as legal, risk, IT, communications, and other analytical experts, who aided, for instance, with behaving in line with the *legislation,* improving the *IT infrastructure, or with* specific knowledge (e.g. HR or facility experts). Due to the focus of this article, we hereafter refer to the function's internal customers as "stakeholders."

Attitudinal differences: Stakeholders could have widely varying attitudes towards people analytics. For example, some were eager to work with the people analytics function, whereas others appeared to avoid it. Similar observations were made for the experts within people analytics, as they also appeared to have a preference for certain stakeholders. This difference in attitude depended primarily on the work setting (*senior manager support, organizational culture, and hierarchical positioning of the function)*, previous experience, and analytical capability of the stakeholder. First, on the one hand, stakeholders' work settings affected their willingness to work with the people analytics function, as PAL9 explained: *"My chief HR officer, you know, when papers go to have decisions, she'll constantly push back, 'Where is the data?' and wanting to see that everything is supported and evidenced."* As a result, stakeholders would often be more interested in working with the function. This same tendency was observed for stakeholders who noticed that business leaders responded favorably to recommendations backed up by logic and numbers. On the other hand, the people analytics function could decide to prioritize working with stakeholders who operated in a certain work setting. For example, some functions preferred to work with business stakeholders over HR, as this allowed them to have an impact on the organizational strategy and because it is *"where most of the company's money comes from"* (PAL4). Therefore, the work setting in which stakeholders operated thus affected their willingness to work with people analytics, and vice versa.

Second, stakeholders' past experiences with people analytics functions affected their attitudes towards each other. If the experience was positive, it could accelerate their collaboration, as TL2 mentioned: *"You know, the other side to that sort is an insatiable appetite for data. You know, people who trust data want more, because if they have more, then they can feel more confident."* However, if the experience was negative, the function and stakeholder could distance themselves from each other, as PAL11 explained: *"if we have a stakeholder that we already know that is not going to accept [our insights]. (...) we wouldn't support them."*

Third, the analytical capability of the stakeholders also affected interactions with the function. For instance, stakeholders with low analytical capabilities could be afraid to work with a people analytics function due to their aversion to mathematics, fear of de-humanizing the HR function or fear of losing their power to people analytics. On the other side of the spectrum, people analytics functions could avoid working with stakeholders with low analytical capabilities, as their questions often related to reporting instead of advanced analytics, and they were viewed as "not ready" for people analytics or had a slower and poorer understanding of the insights provided by people analytics (e.g. the value of "significant differences").

Collaboration: The collaboration process appeared to be one of the most critical processes for the success of a people analytics function and was affected by the aforementioned attitudes of the stakeholders and the inputs of a people analytics function. The collaboration process not only influenced the successful execution of an individual project, but also affected the type of output a stakeholder would ask for (e.g. reporting versus advanced analytics), and even more importantly, the willingness of stakeholders to act on the results. Based on the data, we could distinguish four types of stakeholders who each influenced the collaboration process with the people analytics function in a unique fashion. These four types can be labeled as skeptics, the confused, enthusiasts, and strategists. Skeptics could typically be found within HR and had a negative attitude towards people analytics. Therefore, most skeptics would avoid collaborating with the people analytics function, and when others pushed for it, they primarily approached the function for (data) support on decisions that they had already made, as expressed by PAL10: *"you have all of those possibilities in an interaction with a stakeholder (...) 'Hey, I [stakeholder] have this uhm... project. Can you [people analytics expert] show me that it was a success? The numbers.'"* As a consequence, skeptics would also often ignore insights that did not match their views. People analytics functions typically tried to avoid collaborating with these stakeholders or gave in to their demands when this was impossible (e.g. due to the seniority of a manager).

The confused type could also primarily be found within HR and had low analytical capabilities. They hence saw people analytics experts as "wizards" and appeared to

be confused about what benefits people analytics could bring them, as described by one of the stakeholders: *"everybody has a very clear stigma around what it [people analytics] is (...) they [the people analytics function] produce graphs (..) they make our [HR] strategic slides look prettier because they put numbers in them. And I don't think we want to tarnish them with that label. They're a real service, and I think that's what they need to be seen as (...) and I think people should realize that's something you can tap into, and we don't tap into it enough"* (HR3). This confusion often resulted in them requesting basic reporting questions, which caused people analytics functions to spend more time than they would have liked on basic reports. Therefore, they worked to improve the analytical capability of their stakeholders.

Enthusiasts typically had a positive attitude towards people analytics and were eager to initiate projects with the function. However, they cared more about satisfying their own curiosity than taking action, as illustrated by TL2: *"You know, so sometimes the business questions that we're answering are based on curiosity and not necessarily a desire to act."* While collaborating with stakeholders, it would often be investigated upfront whether there was a potential action to be taken as a consequence. That is not to say that an action had to be taken, as sometimes this could prove to be difficult due to factors such as sensitivity, impossibility, and timing.

Strategists were generally viewed as the ideal stakeholders. They had a positive attitude towards people analytics and were often senior managers themselves. This meant they were both able and willing to act on the insights provided by the people analytics function. Strategists could ask questions around the strategic priorities of HR or the business, as a senior HR manager explained: *"...Helping you [HR] to determine what you need to do (...) you know, a really good, distinctive people strategy, does need to be evidence-based"* (HR1). Alternatively, strategists could be sought out by people analytics. Collaboration with the strategist would typically be a "collaboration from A–Z" in which both parties supported each other (see also partnerships below).

Partnerships: Establishing partnerships also appeared to be a critical process for people analytics functions to ensure that their insights were effective, accepted, and implemented. As we already touched on the acceptance of the insights provided by people analytics functions in the previous section, and since the implementation is mostly left to the stakeholders, in this section we focus on the ways in which partnerships helped functions to be more effective. First, stakeholders are an important source of new projects. Second, stakeholders can help to prioritize which people analytics project would best serve the business needs, as illustrated by PAL4: *"I prefer to spend most of our energy focusing on those things that ehm, that the business finds urgent."* Third, they can also help scope projects and identify data sources that people analytics experts may be unaware of. In the same vein,

especially senior leaders can also help to access this data. Fourth, stakeholders may help to contextualize the results or think of variables to include from a business perspective. Fifth, better follow-up actions are designed when people analytics experts and stakeholders jointly decide on follow-up actions *"because it's better to have that perspective [of people analytics] when we're thinking about changes" (M1).* In conclusion, establishing partnerships is critical for the success of the outcomes of a people analytics function and its sustainability.

Transparency: A particular behavior, namely, transparency, also appeared to be a stakeholder process and was related to the projects, analyses, data, and working method of people analytics functions. First, many interviewees mentioned that they were open about the projects the people analytics function executes, but that this transparency has its limits: *"I think in order to sort of get that legitimacy amongst our peers and... and stakeholders is just to continue displaying this... this behavior. Being as transparent as we can. Without divulging anything that shouldn't be divulged [for confidentiality reasons]"* (PAL10). Second, it was noticeable that people analytics functions were quite transparent about the limitations of their analyses. For example, interviewees mentioned that they were open about the limitations of predictive and prescriptive analytics and were often openly not in favor of prescriptive analytics, as advocated by TL1: *"all these results are ehm, they are true on average (...) I think, the difficulty for many people. To understand. That we cannot, we won't, we will never do this. Ehm. Predict individual behavior. But we can eh, can make a decision."* Third, people analytics functions were transparent about the data. On the one hand, this suggests that they were transparent to stakeholders about the analyses they could not perform due to issues with the data. On the other hand, it also implies transparency to employees about what their data is used for. This transparency was also advocated by PAL4: *"although there is a lot of excitement about the ability to use digital exhaust and tracking online behaviors, or people's comments, or something, we stay far away from those things that would feel potentially invasive to our employees. And then, instead, would directly ask questions in the form of a survey rather than essentially spying over people's shoulders."* Fourth, interviewees also indicated that they were transparent about their working methods, for instance in relation to the assumptions and algorithms that are used.

Outputs of the people analytics function

The people analytics functions included in this research generally delivered three types of output. First, they provided tangible products, such as reports, advanced analytics models, surveys, and efficiency tools, to their stakeholders. Second, they offered intangible services by conducting research and offering consultancy. Third, they enhanced their own reputation as well as the capabilities of their stakeholders. Table 3.4 contain illustrative examples of each of these outputs.

Table 3.4. Illustrative quotes of the outputs of a people analytics function

Product	Example
Reporting	*"I would have to say that the most impactful insights or reports or apps or whatever the team produced are those that contribute to the KPIs that we've set that contribute to those goals or whatever"* (PAL8). *"You can now get all this information on your cellphone. And you know, I kind of joke with them. And this has been the used case, has been when people are in meetings. And they see a number. And they want really quickly and sort of anonymously, to check a number. They are now able to use their phone and go in and see this information pretty quickly. And it's that kind of thing that transforms the way people are doing things. And ehm, and it's funny. When we look at our use of statistics. We are finding a lot of the people that we never get attention from. Or, are organically going"* (PAL5).
Advanced analytics	*"Strategic workforce planning is one field where we can ehm, do as we want. So, there we can apply all our methods. Ehm. And there we can bring up good decisions. Ehm. Because what we do is. We simulate ehm, our FTE's. Our head counts over years. The idea is to look in the future. Which jobs do we need, and which jobs do we have? They are maybe a gap. And we have to fill this gap. And ehm, when these are key positions, we have to act now"* (TL1). *"One of the best projects I think we delivered last year. It could predict ehm, certain risk and insights within X [company name]. With a predictive model that was trained for couple of years. So, the final result is now their stakeholders having a mobile app. But they can actually understand how certain things gonna change in the future. Depending on how things are trending now"* (PAL2).
Survey (design)	*"… all of our employee surveys and assessments. Eh… and they are about recruitment, leadership, competencies eh… and employee satisfaction research, the whole range"* (PAL3) *"It just also ensures that the quality of the surveys within the organization, if you just design it yourself with professionals. Because that is something you see within [company name] more and more. Of course this is very positive, that they make surveys more increasingly so, really… eh… data-driven, in a way that it is eh… reliable and valid and such".* (DA1)
Efficiency tools	*"So, instead of taking two weeks to do something, for example, you can do it in half a day (….) You would have to do some kind of extraction and then three of four transformations. And each individual layer on two dozen, or whatever, business is going to do it slightly differently. And come back with numbers that don't really agree. So, it is highly manual and highly resource intensive and highly eh, variable. And so, we've added some, added some standardization to that. And also, got speed."* (PAL4)

Service	Example
Research	*"I studied the culture of that sales force quite intensively. Ehm. To the point where I was flying off, and ehm. Visiting and shadowing members of our sales team. (...) Having done those kinds of observations, I realized that there is no way, I could have done it anyway near as well. If I had not done it, gone along on those trips"* (PAL2). *The business was complaining that a lot of time was being spent in calibrations [for performance scores] (...) we decided to start a pilot with them where OK, we're going to try to figure out whether there's any consistency to these performance scores (...) We removed the, the performance score erm, we anonymised it and then we send it to different managers (...) What we found out was there's basically, erm, performance scores were random (...) which obviously caused major impact when we presented these results"* (PAL11).
Consultancy	*"One [people analytics sub-team] is specifically focused on organisation where they look at organisational effectiveness, support, organisational design, very much act as partners to the business in terms of helping HR teams improve their access to organisational effectiveness tools, metrics, and the things they can use to actually create successful organisational science and scenario planning, challenge things like productivity, cost to the organisation, so they can make, really do design calls"* (PAL9). *"They [the people analytics function] almost are like coaching us [stakeholders] through every change and whatever delivery we are doing. To help to get to actually the outcomes that we are really aiming for. Like: why this new [performance management] cycle? Why do you have feedback available? Why do you have calibration meetings? What do you actually want to achieve? And then, when we have long-term goals clear, then they help us get a measure"* (HR2).

Other	Example
Reputation	*"It's not just one analysis, what it is, is the ehm.. combined effort of the business understanding what is important as well as understanding and trusting the results that they get (...). Reputation is, is key. Both as an individual as well as a team. You have to be known for doing good strong work"* (TL2). *"I think what we need to do really well now and the team, we'll probably start doing is explaining more or showing their value-add as a team what they [the people analytics team] can provide, and how, how, how that can be used."* (HR3).
Analytical capability	*"One of the tasks for our [people analytics] team is also the, eh, educate, and create awareness about data and analytics"* (DA1). *"We try to convince. The only thing we can do is ehm, to, to ehm, make reportings. Ehm. Showing figures that are easily to understand. Ehm. And on the other hand, would have a higher impact. Ehm. So, people can see, in very short time ehm, what is the benefit of it. Ehm. When you have very complex eh, measures, ehm. People won't understand it. Ehm. They won't understand it. And sometimes, as I said, I have the feeling they don't want to understand it"* (TL1).

Reporting: The functions typically generated a number of reports for their organization. These reports varied from non-interactive PowerPoint slides to fully customizable reports in which the user could slice and dice the information according to their specific needs. Important elements for reports appeared to be the opportunity to benchmark the scores, the chance to track KPIs, and the "self-service" feature. The latter implies that stakeholders could customize and generate their own reports, for example for a specific business line, without the direct involvement of a people analytics expert. The autonomous generation of reports allowed the people analytics function to save time, while stakeholders could easily access the data relevant to them.

Advanced analytics: The people analytics functions included in this study used various types of advanced analytics, such as regression (also called root-cause analyses in practice) as well as predictive, prescriptive, and autonomous analytics (e.g. text analysis), to determine why certain employee behavior occurred, how to influence it, and how to predict it in the future. Practically speaking, they could investigate, for instance, what caused employees to leave the organization in the past and what actions are most effective for reducing turnover in the future, and they could predict employee turnover yet to come. Although many people analytics experts mentioned that they would like to spend more time on advanced analytics, they were also cautious about using prescriptive and autonomous analytics. These types of analytics can be used to tell decision makers what to do or, in case of autonomous analytics, replace humans (in the decision-making process) all together. The reason behind their caution, is that people analytics experts believe the human decision element to be irreplaceable. Furthermore, they also believed their time is currently better spent on other projects that generate more impact. Nevertheless, under certain conditions, they could see the benefits of using autonomous analytics. DA2 stated the following in this regard: *"AI might disrupt it rather than help it at times is what I think, but yeah, we can use AI in terms of easing the HR operations side and also automating few of our regular HR analyses stuff like turnover, which is a very important metric for any organization."*

Surveys: All people analytics functions in this study were involved in the creation, execution, and/or analysis of employee surveys. These surveys could be large annual surveys, short and frequent surveys (e.g. "pulse surveys"), focused surveys (e.g. dedicated to employee benefits), and employee assessments. Furthermore, aside from closed-ended questions, they could also consist of open-text questions to uncover "*the reasons behind the numbers*" (PAL9). Although some people analytics experts did not consider employee surveys to be a "core people analytics product," as it involves relatively little data science expertise, it also appeared to be one of the most visible and impactful outputs of the function. This was because they were typically

conducted among a large body of the workforce and provide relevant insights for (senior) stakeholders.

Efficiency tools: People analytics functions also created products to automate a proportion of their own work or that of stakeholders. For themselves, functions could, for instance, automate either the process of importing data or the data transformation processes for combining data from different sources. For the stakeholders, tools that automate stakeholders' work were mentioned, such as the creation of a system that suggests automatic replies to e-mails. In both cases, the rationale appeared to be efficiency gains. However, in general, the creation of these types of tools did not appear to be the focus of the functions, as they were only mentioned in a few interviews.

Research: The people analytics functions studied in this research also supported their stakeholders through research. Concretely, they (co-)designed (experimental) research designs, formulated hypotheses, gathered data, and tested whether the hypotheses were confirmed or rejected. Topics that were studied related to the effectiveness of HR practices, the existence of a gender-pay gap, the drivers of employee performance and engagement, and many more. Furthermore, the research methods ranged from quantitative, which was often combined with advanced analytics, to qualitative studies and also included mixed methods. Noticeable was that some companies approached this in an (almost) academic manner and set up research with an experimental and control group to answer the stakeholders' questions in the best possible way.

Consultancy: All people analytics functions fulfilled the role of internal consultants to their stakeholders. This was deemed to be one of the most valuable – and time-consuming – tasks of people analytics experts. In general, they offered four types of consultancy. First, they provided council and aided in measuring the progress of their stakeholders' strategic priorities. Second, they would help their stakeholders think about their problems and assist them in asking the right questions. By doing so, the experts helped their stakeholders to consider the "question behind the question" and connect the issue to the wider organization (i.e. instead of only HR). Third, people analytics experts would raise issues by, for instance, highlighting which departments were likely to experience shortages in the future. Fourth, they could also provide specific data-based recommendations to stakeholders, such as the optimal span of control for managers in a certain functional area.

Reputation: The internal reputation of the people analytics function also appeared to be an important output. This specifically related to the function's credibility and visibility from the stakeholders' perspective. In general, this credibility concerned the expertise of the people analytics experts, the data and analyses they use, and

the way in which their insights are reported (e.g. the numbers should add up to 100% exactly instead of, for instance, 99.98%) and presented. If the people analytics function was seen as credible, then stakeholders would be more likely to believe the insights provided through the aforementioned products and services. The visibility of the function was another aspect that affected its reputation and appeared to be primarily related to the products and services it delivered. Although some of the products had high visibility, such as surveys and reports, others tended to be less well known within the organization. The result was that people analytics functions were not particularly visible with respect to the other work they performed, such as their advanced analytics or research. The people analytics functions included in this research were therefore carrying out various activities to raise awareness among stakeholders, including organizing meetings in which they would showcase successful projects or sending out newsletters. This, they hoped, would *"win [stakeholders'] hearts and minds a little"* (PAL2), which would be helpful for future collaborations. Interestingly, improving visibility was also one of the most significant improvement points that stakeholders mentioned.

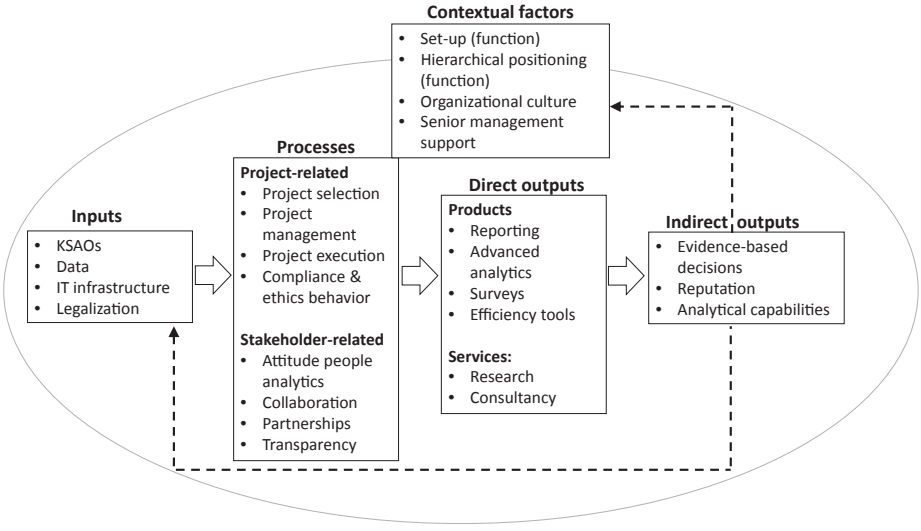
Analytical capability: All people analytics functions worked to improve the analytical capabilities within their organizations. This activity primarily focused on HR experts, as their analytical capability generally appeared to be low and was a prerequisite for the analytical culture. People analytics functions were investing in this for two primary reasons. First, as HR experts typically prioritize humans over numbers and rely on their own expertise, some had a negative attitude towards analytics (skeptics). This led them to ignore the benefits that people analytics could bring to the HR function. Second, as people analytics is a novel field, many HR professionals were also unsure (confused) about what these benefits were. To raise awareness and the likelihood of HR acting on the insights provided by people analytics, the function focused on increasing the analytical capabilities of their HR stakeholders through training and internships. Furthermore, they also tried to highlight the benefits by demonstrating successful previous projects to their stakeholders. Finally, another method involved people analytics experts working with stakeholders to improve their analytical capabilities and show them the results.

Discussion

The aim of this article was to summarize our findings in a heuristic framework that can be used as a first step towards the development of a conceptual model on people analytics effectiveness. For this purpose this article a) examined the relationship between the different elements a people analytics function requires, b) provided insight into the inputs, processes, and outputs that a people analytics function requires to be effective and c) included the viewpoint of the recipients of these outputs, the stakeholders of a people analytics function. An explorative study in

which we completed 36 in-depth interviews with people analytics experts and their stakeholders from nine different multinationals was therefore conducted. In this section, we further reflect on and refine our empirical findings by formulating seven propositions, which result in the *people analytics effectiveness model* (see Figure 3.1). This model represents a more specific application of the general IPO model to depict the variables that play a role in the effectiveness of a people analytics function. Below, we explain this model and summarize the implications thereof in the form of propositions.

Figure 3.1. People analytics effectiveness model



1. Inputs vary in their relative importance and effects

Based upon our results, we identified various inputs of a people analytics function. These elements are largely in line with other models on people analytics (e.g. Guenole et al., 2017; L. Liu et al., 2020; Opatha, 2020). However, to the best of our knowledge the input "legalization" has not been identified before. Furthermore, although other models on people analytics effectiveness have identified these other inputs before (e.g. Ferrar & Green, 2021; Guenole et al., 2017; L. Liu et al., 2020; e.g. Opatha, 2020; Peeters et al., 2020; Shet et al., 2021), no model has thus far combined them all within a single model. Therefore, the overview presented within this paper seems more complete compared to prior work.

Some of the inputs we identified appear, however, to be more necessary and more closely related to the function than others. The input "legislation," for instance, appears to be highly relevant because it determines if and when a people analytics

function would break the law. As such, compliance with this particular input appears to be a license to operate. Other inputs, such as the "KSAOs," "data," and "IT infrastructure," are self-evidently "must haves" for a function to generate its outputs. In contrast, other inputs, such as "senior management support" or "organizational culture," appear to relate more to the way in which the people analytics function was embedded in the organization and the context in which it operated. Although these inputs aid a people analytics function when present, they mostly do not hinder the function when absent and could therefore be considered "nice to haves." Although we describe these contextual factors as inputs in line with the IPO model (Kozlowski et al., 1999; Mathieu, Maynard, Rapp, & Gilson, 2008), we believe it would be more appropriate to make a distinction between the inputs that are directly related to the function and the contextual factors. Based on the above, we make the following propositions.

Proposition 1: The inputs of a people analytics function can be categorized into "license to operate" (legislation), "must haves" (KSAOs, data, IT infrastructure), and "nice to haves" (senior management support, organizational culture). If the license-to-operate and must-have inputs are not present, then the people analytics function is unable to transform any inputs into outputs. Nice-to-have inputs will ensure a smooth transformation process and that the outputs are more accepted and effective.

Proposition 2: Contextual factors, such as the set-up and hierarchical positioning of the people analytics function, management support, and organizational culture, influence the way in which inputs are transformed into outputs. If more favorable contextual factors are present in the organization in which a people analytics function is imbedded, then the inputs will have a higher chance of being transformed successfully into outputs.

2. Two types of processes exist: project- and stakeholder-related processes

Based on our data, a people analytics function requires a variety of processes to successfully transform its inputs into outputs. In line with other models on people analytics effectiveness (Guenole et al., 2017; Peeters et al., 2020; Shet et al., 2021), a number of these processes are directly related to the way in which people analytics projects are executed. Specifically, project selection, management, execution, and the compliant and ethical behavior of people analytics experts during all of these stages are identified as important processes. The latter, compliant and ethical behavior of people analytics experts, have rarely been included by other models in the past (save for perhaps Peeters et al., 2020 who discussed the need for a people analytics function to be seen as legitimate).

Other processes relate to the stakeholders and whether they could accept and act on the insights provided by the function (Greasley & Thomas, 2020; Pachidi, Berends, Faraj, & Huysman, 2020; Vargas et al., 2018). In particular, the attitudes of stakeholders (and people analytics experts), collaborations, partnerships, and the transparency of the people analytics function towards their stakeholders are important processes. From the currently available models, only two broadly identify "stakeholder management" (Ferrar & Green, 2021; Peeters et al., 2020) and one specifically lists the attitude of stakeholders as crucial (Shet et al., 2021). Most of the stakeholder processes we identify are consequently new additions to the literature. All in all, we distinguish based upon our results two important categories of processes for a people analytics function. This leads to the third proposition:

Proposition 3: Two types of processes exist, namely, project-related and stakeholder-related, processes, which a people analytics function requires to transform inputs into high-quality outputs that are accepted and acted on by stakeholders.

3. Stakeholders vary in their attitudes and usage of people analytics

In line with Greasley and Thomas (2020), we found that stakeholders had different attitudes towards people analytics and used the insights in different ways. In other models on people analytics effectiveness, only Shet et al. (2021)'s model briefly mentions this process. Based upon our results, we were able to provide in-depth insights into this crucial process to a people analytics function. Specifically, we distinguished four types of stakeholders: skeptics, the confused, enthusiasts, and strategists. Skeptics have a negative attitude towards people analytics and would, if pushed, only seek to obtain (data) support on decisions they have already made. Confused stakeholders are unaware of the benefits that people analytics could bring, due to their own low analytical capability, and they primarily request basic reports. Enthusiasts have a positive attitude towards people analytics, but they are primarily interested in satisfying their own curiosity instead of taking actual action. Strategists are the ideal type of stakeholder, as they have a positive attitude towards people analytics and collaborate with the function on strategic issues. As Guenole et al. (2017) recommended, we believe that people analytics experts should use different tactics to work with these stakeholder types effectively. For instance, a people analytics function could avoid working with skeptics (when feasible), educate the confused, enquire about the decision an enthusiast aims to make, and intensify collaboration with strategists. Based on this, our fourth proposition is as follows:

Proposition 4: The stakeholders of a people analytics function can be subdivided into skeptics, the confused, enthusiasts, and strategists. To transform inputs into outputs, different tactics are required when dealing with each stakeholder type.

4. Direct and indirect outputs

Similar to other models on people analytics (Ferrar & Green, 2021; Guenole et al., 2017; Opatha, 2020; Peeters et al., 2020; Shet et al., 2021), our results indicate that a people analytics function creates a number of products and services for its stakeholders, such as reporting, advanced analytics, and research. However, people analytics experts can only empower stakeholders to make evidence-based decisions; they can neither make those decisions on their own, nor enforce them. For a people analytics function to be truly effective, it must thus ensure that stakeholders utilize its outputs for decisions (Guenole et al., 2017). It can consequently be argued that the products and services are direct outputs of a people analytics function, while evidence-based decision-making by stakeholders is an indirect output. Additionally, the people analytics functions we studied invested substantive effort in building both their reputation and the analytical capability within the organization. They could do this by producing (high-quality) products and services or by organizing, for example, trainings (direct outputs). Therefore, the reputation and analytical capability of an organization appear to be indirect outputs, which support the effectiveness of a people analytics function. This distinction, and the indirect outputs reputation and capability building, seem, to the best of our knowledge, not to have been identified by other models on people analytics effectiveness before. Based on the above, we make the following two propositions:

Proposition 5: The effectiveness of a people analytics function is determined by the extent to which stakeholders use the function's outputs to make tactical and strategic decisions.

Proposition 6: The people analytics function produces direct outputs (i.e. products and services) and indirect outputs (i.e. evidence-based decision-making by stakeholders, reputation, and analytical capability).

5. Feedback loops

In an adapted version, Mathieu et al. (2008) proposed that outputs may also turn to new inputs and added a feedback loop to the model. Similarly, we believe that an IPO-model on people analytics also should have feedback loops, as the function dynamically changes and evolves based on previous projects and collaborations. For instance, by delivering valuable outputs, people analytics can enhance its own KSAOs and receive permission to recruit new members. In addition, outputs such as the analytical capability of stakeholders are likely to affect the context in which people analytics operates, since stakeholders are likely to become more interested in working with people analytics experts as their capabilities grow and they hence become more inclined to use their outputs to make evidence-based decisions. Although there are hints towards the existence of these feedback loops in the work of for example Guenole et al. (2017) and Ferrar and Green (2021), our framework is, to the best of

our knowledge, the first one to clearly distinguish these feedback loops. Therefore, our final proposition is as follows:

> *Proposition 7: A people analytics function dynamically changes and evolves over time such that the outputs of the past influence the inputs and organizational context in the future.*

Limitations and future research

This research has a number of limitations. First, we interviewed a relatively small number of people, all from multinational organizations that already had relatively advanced people analytics functions. Although this allowed us to gain in-depth insight into how a people analytics function evolves over the years, it also meant that we may have missed the struggles of a newly established people analytics function in smaller organizations. Second, the people analytics leaders directed us to the stakeholders we interviewed, and not all stakeholders agreed to be interviewed. This likely means that we primarily spoke to stakeholders who had positive experiences with people analytics, and not those who may have been more skeptical. Third, the data we collected was cross-sectional, and we thus only obtained a snapshot of all the people analytics functions we studied for this research. Therefore, we have limited knowledge of how the function evolves from a more dynamic perspective and how the context of people analytics affects its effectivity. We consequently encourage scholars to initiate large-scale, longitudinal research that incorporates people analytics functions from different sectors to test and extend our theoretical model.

Conclusion

In this article, we developed an empirically grounded framework with seven propositions that explains how a people analytics function may effectively contribute to evidence-based decisions regarding the workforce and the business. By doing so, we believe that the field is one step closer to ensuring that people analytics can create business impact and enable data-driven decision-making. The next step is to test these propositions in practice and further advance our theoretical knowledge in this area.

4

The effects of the agile way of working on team performance and engagement

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Abstract

Purpose: This study examines the relationship between the agile way of working and team performance and engagement. Furthermore, psychological safety climate was investigated as a mediator of this relationship. As organizations are increasingly adopting the agile way of working method beyond the Information Technology setting, we researched its effects in teams across a variety of functional domains.

Design/methodology/approach: Survey data was collected from 97 agile teams working in various functional domains in a multinational bank. The data was analyzed using structural equation modeling.

Findings: Results indicated that the agile way of working is directly and positively related to team engagement and performance. Moreover, psychological safety climate acted as a partial mediator of each of the respective outcomes.

Originality/value: This study illustrated that the agile way of working is beneficial for teams beyond the Information Technology setting, as it is positively associated with psychological safety climate, engagement, and performance across functional domains.

Keywords: Agile, psychological safety climate, team engagement, team performance

Paper type: Research paper

Introduction

Based upon a belief that software development teams should be more collaborative and client-focused (Wood, Michaelides, & Thomson, 2013) in order to respond to the volatile, rapidly changing environment (Gren, Goldman, & Jacobsson, 2020; M.-L. Liu, Liu, Ding, & Lin, 2015) and to maintain high productivity, innovation and software quality (Grass, Backmann, & Hoegl, 2020; Melo, Cruzes, Kon, & Conradi, 2013; Papatheocharous & Andreou, 2014), the agile manifesto has been written almost two decades ago (Beck et al., 2001). According to this manifesto, teams should be self-managing, self-reflective, have a quick product turnaround, make efficient use of their resources, work in close collaboration with their stakeholders, and interact primarily through face-to-face communication (Beck et al., 2001). The resulting agile teams are defined as small, democratic and cross-functional teams in which members are empowered to take collective decisions and do not have strict hierarchies in place (Hoda, Noble, & Marshall, 2012). Nowadays, the agile way of working has become common practice among information technology (IT) teams. As this particular method of working is believed to be beneficial for teams regardless of the teams' functional areas, other domains such as sales have begun to implement the agile way of working too (Edmondson & Gulati, 2021; Mergel et al., 2018).

The rationale behind the benefits of the agile way of working is often explained through its agile work practices. For example, as a team becomes more self-managing, it is argued that team members have more leeway to complete tasks in line with customer requirements thereby resulting in better products, quicker product delivery and more positive feelings among employees about their work (Grass et al., 2020). As such, agile way of working can intrinsically motivate employees to perform (Malik, Sarwar, & Orr, 2021), facilitate employee engagement (Khanagha, Volberda, Alexiou, & Annosi, 2021) and boost employee satisfaction (Tripp, Riemenschneider, & Thatcher, 2016). Although a few empirical studies have demonstrated a link between agile ways of working and team performance within the IT sector (e.g. Melo et al., 2013; Ramirez-Mora & Oktaba, 2018; Wood et al., 2013), little is known about the effects of the agile way of working in other functional domains (Hobbs & Petit, 2017). This is problematic as the context in which the agile way of working is successful, the so-called "agile sweet spot", is very specific in terms of team size, tasks involved, organizational culture and setting (Kruchten, 2013). As a consequence, there have been warnings that the agile way of working may not be suitable (Edmondson & Gulati, 2021) or even fail (Kruchten, 2013) when taken out of its (IT) context. Nevertheless, as organizational role models such as Netflix, Spotify and Amazon have embraced the agile way of working (Rigby et al., 2018), there is an ever-increasing adoption rate of the agile way of working among organizations operating within and outside of the IT-context (Edmondson & Gulati, 2021). In this paper, we therefore investigate the effects of the agile way of working among teams across a range of functional domains.

As increased performance levels are one of the primary motivations to implement the agile way of working, we will firstly empirically assess the impact of agile ways of working on team performance. Second, as the agile way of working is believed to be linked to increased levels of engagement by actively involving team members in their work (Malik et al., 2021), and many organizations are actively striving for an engaged workforce (Berkey, 2019), we will also assess its effects on team engagement. Team engagement refers to a positive, fulfilling, and motivational state of work-related well-being which is characterized by team members having high levels of energy (vigor) in performing their collective tasks and being enthusiastic and involved (dedicated) in their work (Tims, Bakker, Derks, & Van Rhenen, 2013).

Moe, Dingsøyr, and Dybå (2010) argue that the agile way of working results in certain team interactions and dynamics which are beneficial to team performance and engagement. However, remarkably little empirical research has been devoted to understanding how the agile way of working positively influences team outcomes (Fagerholm et al., 2015). Therefore, our third objective is to advance knowledge on "why and how" the agile way of working leads to beneficial outcomes (Malik et al., 2021 p. 10). Recently, it has been argued that psychological safety climate, a positive team dynamic frequently found to be predictive of team engagement and performance within the team literature (Frazier, Fainshmidt, Klinger, Pezeshkan, & Vracheva, 2017), is a key factor in explaining agile teams' success (Buvik & Tkalich, 2022). Psychological safety climate is a shared belief among team members that they can take interpersonal risks and can, for instance, be open about their mistakes (Edmondson, 1999). Based upon the previous, this study investigates whether psychological safety climate may indeed be an important emergent state that explains how the agile way of working leads to enhanced team performance and engagement.

In sum, by examining the impact of the agile way of working on team engagement and performance via psychological safety climate among teams from various functional domains, this study contributes to further understanding what teams may gain from adopting the agile way of working and explain the underlying mechanisms involved. In addition, although this study builds on insights from the teams' literature to explain how practices inherent to the agile way of working (e.g., self-management, reflexivity) result in team outcomes (Konradt, Otte, Schippers, & Steenfatt, 2016; Magpili & Pazos, 2018; Mathieu et al., 2008), it also adds new insights. Specifically, the agile way of working is argued to offer teams a way to strategically deal with the fast-changing environment in real-time (McKinsey&Company, 2018) through a combination of agile work practices that mutually reinforce each other. As such, we will not examine the unique effect of any specific agile way of working practice on team outcomes (as is common in teams literature). Instead, we will investigate whether the combination of agile way of working practices (as one concept) lead to beneficial effects for teams operating in fast-changing environments. From a practical point of view, organizations

can use our findings to validate their beliefs about the potential benefits of the agile way of working on top of the anecdotal stories provided by renowned tech firms like Netflix and Spotify (Rigby et al., 2018). Furthermore, practitioners can use our findings to assess whether the current trend to adopt the agile way of working beyond their IT department (Mergel et al., 2018), is a viable strategy supported by empirical evidence. Finally, our findings will help practitioners gain more insight into why the agile way of working may lead to beneficial team outcomes.

Theoretical framework

The agile way of working

To pursue the team characteristics recommended by the agile manifesto, agile teams typically use various agile practices. For example, to achieve quick product turnaround, agile teams typically plan their work in "sprints" (i.e. brief, predetermined time periods) of a few weeks and have a "retrospective" meeting after every sprint to reflect upon their functioning (Espinosa-Curiel, Rodríguez-Jacobo, Vázquez-Alfaro, Fernández-Zepeda, & Fajardo-Delgado, 2018; Tripp et al., 2016). However, agile practices can be applied in many ways. For example, the sprint can differ between teams in duration and approach (Gren et al., 2020; Papatheocharous & Andreou, 2014; Tripp et al., 2016). To make matters even more complex, Hess, Diebold, and Seyff (2019) found that teams use different agile practices and value them in different ways. Consequently, large differences between how teams utilize agile practices exist. Therefore, in the current paper, we focus on the core team characteristics which the agile manifesto recommends (Beck et al., 2001), and which are also consistently mentioned in the agile team literature (Espinosa-Curiel et al., 2018; Grass et al., 2020; Gren et al., 2020; M.-L. Liu et al., 2015; Moe et al., 2010). These practices are self-management, face-to-face communication, reflexivity, product turnaround, simplicity, and customer interaction.

First, self-management refers to the ability of the team to make their own decisions about their work. Second, face-to-face communication is seen as the primary form of team communication and refers to the frequency and quality of face-to-face interactions among team members. Third, product turnaround refers to the frequency, consistency, and sustainability of the team's delivery of outputs. Fourth, team reflexivity refers to the ability of the team to (regularly) reflect and learn from their previous experiences. Fifth, simplicity is defined as "the art of maximizing the amount of work not done" (Beck et al., 2001) and relates to only spending resources on tasks that have added value. Sixth, frequent and close collaboration with customers is advocated by the agile manifesto. It focuses on clarifying what the customer wants and needs, thereby enabling teams to spend their resources accordingly (Beck et al., 2001). As the explanatory mechanism studied in the present study, psychological safety climate, is focused on internal team dynamics, the externally focused customer

interaction dimension will not be considered. We use "the agile way of working" to refer to the first five core characteristics. These five characteristics can mutually reinforce each other, because team reflection, for instance, is typically of higher quality when it is done face-to-face (Marques-Quinteiro, Uitdewilligen, Costa, & Passos, 2021), as it allows teams to get to the root of a potential problem (Otte, Konradt, Garbers, & Schippers, 2017). As a result, it can be argued, in line with Otte, Konradt, and Oldeweme (2018), that face-to-face team reflection is more likely to result in increased team communication in comparison to teams who reflect through another method. Therefore, we will study the effect of the set of agile practices on team outcomes. This approach is also in line with the literature on human resource management (e.g. K. Jiang et al., 2012) which suggests that (Human Resources) practices may be interdependent and act in a synergetic way such that their combined effect is greater than the sum of their individual effects. Finally, this bundle of agile work practices will primarily focus on the quality of the agile way of working, rather than the frequency to which teams engage in any of the core activities of working agile (e.g., reflexivity). There are large context-driven fluctuations between how often teams engage in typical agile activities (Hess et al., 2019) and this focus aligns more with the agile principle to provide teams "the work environment and support they need" (Beck et al., 2001).

The agile way of working and team performance

For many companies, the primary motivation to adopt the agile way of working has been to increase their performance (Ramirez-Mora & Oktaba, 2018). We follow the research of Fagerholm et al. (2015) on team performance among agile teams which primarily distinguishes between efficiency (i.e., quickness and minimal use of resources) and effectiveness (e.g., achieving those goals with the highest added value) of the team. Empirical research in the IT sector shows that the agile way of working can improve team performance (Melo et al., 2013; Ramirez-Mora & Oktaba, 2018; Wood et al., 2013), which can theoretically be explained by the core practices of the agile way of working. Concerning team efficiency, it can be argued that due to quick *product turnaround*, the likelihood of team members working ahead of schedule and spending their time on ill-defined and perhaps even irrelevant tasks decreases (Fagerholm et al., 2015). Moreover, as all team members agree upon which goals they would like to pursue during a specific time frame (i.e., sprint), members are enabled to focus on those tasks relevant to achieving the current team goals (*simplicity*). With frequent *face-to-face communication* between members occurs in a way in which any obstacles and requests for help can be discussed, it can be argued that the agile way of working can increase the efficiency of a team (Dingsøyr, Fægri, Dybå, Haugset, & Lindsjørn, 2016; Ramirez-Mora & Oktaba, 2018). Similarly, the agile way of working may also lead to an increase in the effectiveness of the work. As a result of short product turnaround, daily face-to-face communication, and frequent team *reflexivity*, members of an agile team can review their performance daily and adjust

accordingly (Fagerholm et al., 2015; Tripp et al., 2016). In particular, the opportunity to ask each other questions, seek feedback, experiment, and discuss errors is argued by Dingsøyr et al. (2016) to enable the team to learn and improve its effectiveness. Consequently, it can be concluded that the agile way of working could help a team become more efficient and effective. This leads to the first hypothesis.

Hypothesis 1: The agile way of working is positively related to team performance.

The agile way of working and team engagement

In addition to achieving higher team performance, the core characteristics of the agile way of working are also likely to be positively associated with employee outcomes such as team engagement. The research of Grass et al. (2020), for instance, showed that as agile teams become more *self-managing*, they get a better feeling for what it takes to complete a task for a customer in a satisfying manner. As a result, team members have reported feeling more positive about their work. This notion is also supported by empirical work on agile teams (Tripp et al., 2016) and in the engagement literature (W. Schaufeli, 2012). Additionally, it can be argued that due to frequent face-to-face communication and reflexivity, agile team members can form strong personal relationships with each other (McHugh, Conboy, & Lang, 2011), which has been linked to higher levels of engagement (W. Schaufeli, 2012). Although there is, to the best of our knowledge, no empirical support yet for the relationship between the agile way of working and engagement, other affective outcomes such as organizational commitment and job satisfaction have been found to be positively related to the agile way of working (Moe et al., 2010; Tripp et al., 2016). Therefore, we propose the following.

Hypothesis 2: The agile way of working is positively related to team engagement.

The agile way of working and psychological safety climate

The core elements of the agile way of working, such as face-to-face communication, reflexivity, and quick product turnaround (McHugh et al., 2011), have been argued to enhance open, trusting, and honest communication between team members (i.e., psychological safety climate; (Ramirez-Mora & Oktaba, 2018) in prior literature. However, to date, there appears to be only primary support for the relationship between the agile way of working and other related emergent states, such as trust (McHugh et al., 2011) and team cohesion (Wood et al., 2013). Nevertheless, within the psychological safety climate literature, there is support for the assumption that the agile way of working can foster a psychologically safe climate. In their meta-analysis, Frazier et al. (2017), for instance, found that work environments that signal that employees are trusted with important decisions (i.e., self-management), have clarity about their roles, and rely on each other to complete their tasks are important antecedents for enhancing a psychologically safe climate. Furthermore, Akan, Jack,

and Mehta (2020) argue that because psychological safety climate is an interpersonal construct, the conversations within the team influence its emergence. This claim is also supported by the literature review of Newman, Donohue, and Eva (2017), in which the authors find that the extent of interaction, familiarity, the quality of the relationships between team members, and perceived social support, all positively influence the psychological safety climate of a team. As face-to-face communication is advocated as the primary means of communication within agile teams, it can thus be expected that the agile way of working fosters the psychological safety climate within a team. This leads to the third hypothesis.

Hypothesis 3: The agile way of working is positively related to psychological safety climate.

Psychological safety climate and team performance and engagement

Within the literature, there is a large amount of support for the notion that psychological safety climate leads to improved team performance and engagement (Frazier et al., 2017; Newman et al., 2017). Concerning performance, it has been argued that because employees feel that it is safe to take the initiative or make mistakes, members benefit from each other's expertise, learn from past mistakes, and can focus upon the task at hand (Edmondson, 1999; Frazier et al., 2017). Concerning engagement, scholars have argued that teams who value their psychological safety climate may reciprocate in the form of increased levels of engagement, in line with the principles of social exchange theory (Blau, 1964; Newman et al., 2017). Consequently, we expect the following.

Hypothesis 4: Psychological safety climate is positively related to team performance.

Hypothesis 5: Psychological safety climate is positively related to team engagement.

The mediating role of psychological safety climate

In the team literature, psychological safety climate is predominantly viewed as an emergent state that explains how certain (team) characteristics and behaviors influence outcomes like performance and engagement (Mathieu et al., 2008; Newman et al., 2017). The input-mediator-output-input model (Ilgen, Hollenbeck, Johnson, & Jundt, 2005; Kozlowski et al., 1999), which has been used in agile studies (Melo et al., 2013), argues that inputs (e.g., characteristics of a team, like self-management) cause certain states to emerge within the team (e.g., knowledge sharing, psychological safety climate) and eventually lead to positive outcomes such as improved performance and engagement (Ilgen et al., 2005; Mathieu et al., 2008; Melo et al., 2013; Newman et al., 2017). Following this logic, the agile way of working may thus ensure that a more psychological safety climate emerges and, consequently, improve performance and engagement. Based upon this, our final set of hypotheses are as follows.

Hypothesis 6: Psychological safety climate partially mediates the relationship between the agile way of working and team performance.

Hypothesis 7: Psychological safety climate partially mediates the relationship between the agile way of working and team engagement.

Methods

Population and sample

The data[1] for this study was collected in collaboration with a multinational company operating in the financial sector that is recognized as one of the frontrunners of the agile way of working. All teams within this company were eligible to participate in the study regardless of their size, functional domain, or country of origin. A total of 168 teams (*N* = 1,591) volunteered to participate in the study and were promised a self-assessment report if at least five team members filled out the survey.

In total, 945 employees from 143 teams filled out the questionnaire in September 2020. The response rate was 59%. We cleaned this data on careless response styles in line with Leiner (2019) and the R package "Careless" (v1.2.1; e.g., straight lining and rushed responses). The cleaned dataset consisted of 773 respondents in 138 teams. As the hypotheses were tested at the team level of analysis, we also filtered out teams with fewer than four responses to ensure a substantial proportion of the team filled out the survey. This led to a dataset containing 97 teams (*N* = 623 individual respondents). As depicted in Table 4.1, the teams resided in 10 different countries, had an average team size of 10 employees, and worked primarily in IT and retail functions. Furthermore, the teams' agile maturity differed according to their members. In Table 4.2, a number of personal characteristics of the respondents can be found. In line with the overall worker population of this company, the gender ratio of the respondents was almost 50-50, their ages were primarily below 45 years, and the majority graduated from a university.

Table 4.1. Characteristics of the teams (aggregated dataset)

	Number of Teams
Country	
Philippines	27
Romania	36
Czech Republic	5
Netherlands	8
Poland	8
Other*	13
Agile maturity	
Mostly traditional	6
In between	23
Mostly agile	55
Fully agile	13
Functional domain	
Retail	22
Compliance	9
Information Technology	32
Human Resources	7
Mixed	7
Other**	20

N = 97

*Other countries being Spain, Austria, Belgium, France, Italy, and cross-border

**Other domains such as communications and finance or respondents who selected "Other" in response to this question

Table 4.2. Personal characteristics of the respondents (aggregated dataset)

	Respondents
Gender	
Male	51.6%
Female	41.3%
No answer	7.1%
Age category	
16–29	26.7%
30–44	57.4%
45–70	9.3%
No answer	6.6%
Educational level	
College	15.2%
University	65.4%
Graduate school	12.3%
Other	1.6%
No answer	5.5%
Tenure with the team	
Less than a year	30.2%
Between one and three years	45.9%
Between three and five years	7.2%
More than five years	11.6%
No answer	5.1%

N = 623

Measures

We used a combination of newly designed scales based upon the agile manifesto[1] and adapted preexisting scales for this study. Specifically, we shortened and contextualized scales with the help of agile coaches to meet the organization's requirements. Therefore, an exploratory factor analysis was conducted first with all items central to this study using the package nFactors in R (v2.4.1). The expected eight factors were found: reflexivity, face-to-face communication, product turnaround, self-management, simplicity, psychological safety climate, engagement, and performance. All factors had an eigenvalue above 1, but two items from the agile way of working scale appeared to have insufficient factor loadings. These included the items "In

1 © by the organization we collected the data in. For more information about the scales, please contact the first author of this paper.

my team, we change our behavior based upon our past experience" (λ = .321 on the reflexivity scale) and "Within this team, we strive to deliver our products/services frequently (i.e., a couple of weeks)" (λ = .246 on the product turnover scale). Therefore, these two items were dropped from the sequential confirmatory factor analysis (CFA).

The agile way of working: To measure the agile way of working, five subdimensions for the agile way of working were used. The subdimensions of reflexivity and product turnaround were measured using two items. Example items are "In my team, we reflect upon the way tasks are executed" (reflexivity; Schippers, Den Hartog, and Koopman (2007) and "The products/services this team provides are delivered at a constant pace" (product turnaround). The self-management, face-to-face communication, and simplicity subdimensions were measured using three items each. Example items are "In this team, we determine amongst each other what needs to be done" (self-management; Kirkman, Rosen, Tesluk, and Gibson (2004)), "Within this team, we value (virtual) face-to-face conversations" (face-to-face communication), and "Within this team, we minimize the amount of unnecessary work that we do." The items were designed based upon the agile manifesto (Beck et al., 2001) and interviews with agile coaches from the company. Like all other items within this questionnaire, the items were scored on a 7-point Likert scale ranging from totally disagree (1) to totally agree (7).

CFA was performed (using the package Lavaan, v.06-8 in R), and we calculated the fit of a second-order model in which the individual item scores (observed variables) were used to estimate their latent variable (e.g., self-management). These dimensions, in turn, were used to predict the second-order latent factor, the agile way of working. The resulting model showed a good model fit (*CFI* = .972, *RMSEA* = 0.052, *SRMR* = 0.041; (D. Hooper, Coughlan, & Mullen, 2008). Furthermore, all sub dimensions loaded sufficiently on the agile way of working second-order construct (reflexivity, λ = 0.71; product turnaround, λ = 0.69; self-management, λ = .67; face-to-face communication, λ = .78; simplicity, λ = .75). The internal consistency of the agile way of working (α = .87) and the subscales (reflexivity, α = 0.84; product turnaround, α = 0.82; self-management, α = .79; face-to-face communication, α = .78; simplicity, α = .79) were good.

Psychological safety climate: To measure psychological safety, three items from the scale from Edmondson (1999) were adapted. An example item is "In this team, members are open about their mistakes." As the scale consisted of three items, the CFA returned perfect model-fit indicators. The factor loadings were sufficient (average λ = .74) and the internal consistency of the scale was good (α = .78).

Engagement: Engagement was measured with three adapted vigor and dedication items from the scale of W. B. Schaufeli, Bakker, and Salanova (2006). W. B. Schaufeli and Bakker (2004) argue that vigor and dedication are the core components of engagement. An example item is "Members of this team are enthusiastic about their work." Once again, the CFA returned a perfect model with good factor loadings (average $\lambda = .81$). The internal consistency of the scale was excellent ($\alpha = .84$).

Performance: Performance was assessed using four adapted items derived from van Woerkom and Croon (2009). An example item is "This team delivers high quality." The model-fit indicators of the CFA indicated a near-perfect model fit (*CFI* = 1, *RMSEA* = 0.003, *SRMR* = 0.005) and had good factor loadings (average $\lambda = .85$). The internal consistency of this scale was excellent ($\alpha = .91$).

As factor analyses was used to validate the above scales, we followed the recommendations of DiStefano, Zhu, and Mindrila (2009) and used factor scores instead of the mean scores in further analyses. By using the factor scores, the weight of each item was brought in line with the contribution of the item to its latent factor.

Control variables: Team size and functional domain were used as control variables. First, agile teams are typically small in size (Lindsjørn, Sjøberg, Dingsøyr, Bergersen, & Dybå, 2016), as this is believed to be more beneficial to the execution of agile practices (e.g., self-management becomes more challenging in big groups). Therefore, large team size may negatively affect the effectiveness of agile practices. Second, we controlled for the effects of the functional domain, as the agile way of working originated in IT, which was also the first function to adapt the agile way of working in this organization. Therefore, we controlled for the effects of functional area by asking this (optional) question: "What is your functional group?" Respondents could select 12 different functional domains as answer options (e.g., IT, retail, risk, and other). As the question were asked at the individual level, we used the most common response in a team. This means that if three respondents answered "IT" and two other respondents answered "retail," we assigned this team to the functional group IT. Furthermore, if an equal amount of respondents selected "IT" and "retail," we labeled that group as "mixed." In the end, we created the dummy variables "IT" ($N = 32$), "retail" ($N = 22$), "compliance" ($N = 9$), "Human Resources" (HR; $N = 7$), "mixed" ($N = 7$), and "other" ($N = 20$). The group "other," for example, consisted of teams working in finance or corporate strategy.

Data aggregation

Although all items from our questionnaire referred to the team level, we calculated the intraclass correlation indices ICC(1) and ICC(2) in order to justify aggregation to the team level using a one-way analysis of variance (Bliese, 2000) and the package "multilevel" (v2.6) in R. As can be seen in Table 4.3, all *F*-tests were significant, ICC(1)

values were above .05, and ICC(2) values were above .40. Therefore, we can conclude that there is sufficient agreement between team members to justify aggregation to the team level (Klein & Kozlowski, 2000).

Table 4.3. ICC values

	F-test	ICC(1)	ICC(2)
Agile way of working	1.94***	0.13	0.48
Psychological safety climate	2.54***	0.19	0.61
Engagement	2.07***	0.14	0.52
Performance	1.69***	0.10	0.41

*** $p < .001$

Analysis

We conducted structural equation modeling using the R package Lavaan (v.06-8) to test the conceptual model. Given the proportion of the number of items measuring our study variables on the one hand and the number of cases on the team level on the other hand, we decided to include the agile way of working, psychological safety climate, engagement, and performance scores as manifest variables (i.e., the saved factor scores) rather than as latent variables (i.e., using the items as indicators) in our model to maintain a favorable indicator-to-sample-size ratio. The benefit of using Lavaan is that the package is designed for structural equation modeling and can thus be specified to simultaneously predict all the hypothesized relationships, including the indirect and total effects of the agile way of working on the outcomes.

Results

Table 4.4 shows the means, standard deviations, and correlations of the study variables. In line with our expectations, the agile way of working correlated with psychological safety climate ($r = .80$; $p < .01$) as well as performance ($r = .69$; $p < .01$) and engagement ($r = 60$; $p < .01$). Furthermore, psychological safety climate correlated with engagement ($r = .58$; $p < .01$) and performance ($r = .63$; $p < .01$).

The findings of our structural equation model can be found in Table 4.5. In line with our expectations, we found that the total effect of the agile way of working was positively related to team performance ($\beta = .652$; $p < .01$) and team engagement ($\beta = .624$; $p < .01$). Therefore, our first two hypotheses were supported by the data. Furthermore, as our results showed that the agile way of working is positively related to the team's psychological safety climate ($\beta = .779$; $p < .001$), the third hypothesis was also supported.

Table 4.4. Correlations and descriptives

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11
1. Agile way of working	5.74	0.39	(.76)										
2. Psychological safety climate	5.35	0.65	.80**	(.78)									
3. Engagement	6.05	0.45	.60**	.58**	(.84)								
4. Performance	5.77	0.49	.69**	.63**	.67**	(.91)							
5. Retail	0.22	0.41	.21*	.21*	.17	.30**	1						
6. IT	0.33	0.47	-.01	.17	-.05	-.09	-.36**	1					
7. Mixed	0.07	0.26	.10	.03	.18	.00	-.14	-.20	1				
8. Compliance	0.09	0.29	.13	-.05	.00	.16	-.16	-.22*	-.09	1			
9. HR	0.07	0.26	-.39**	-.32**	-.14	-.27**	-.14	-.20	-.08	-.09	1		
10. Other	0.21	0.41	-.14	-.22*	-.14	-.16	-.26*	-.36**	-.14	-.16	-.14	1	
11. Size	10.29	4.91	-.08	-.08	-.01	.03	.06	-.05	-.06	.08	.17	-.14	1

Note. M and *SD* represent mean and standard deviation, respectively. Both values are based upon the aggregated mean scores.

The Cronbach's alpha is displayed on the diagonal. Values range from 1 to 7 for the scale scores (1:4), where 1 is the lowest score and 7 is the highest score. The functional dummy variables (5:10) range from 0 to 1, and team size (10) refers to the absolute number of people within the team.

* indicates $p < .05$. ** indicates $p < .01$.

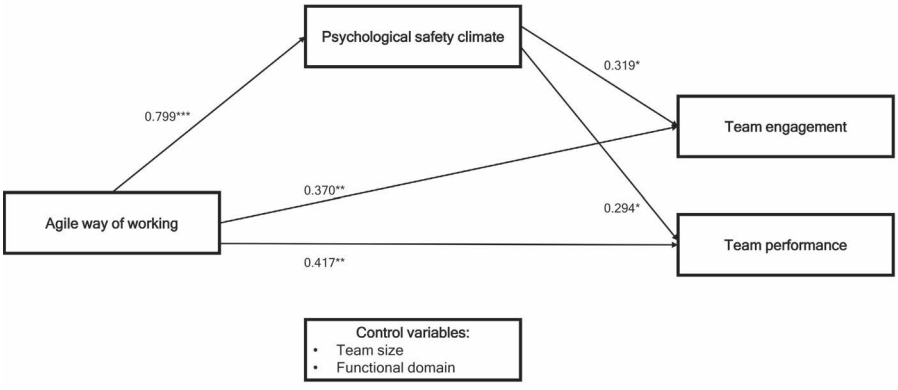
Table 4.5. Results of structural equation model

	Psychological safety climate	Engagement	Performance
Predictor	*B*	*B*	β
Psychological safety climate		.319*	.294*
Agile way of working	.799***	.370**	.417**
Retail	.104	.042	.130
IT	.201**	-.032	-.072
HR	.036	.114	-.012
Compliance	-.081	-.010	.112
Mixed	.001	.142	-.029
Size	-.015	.036	.066
Total effect of agile working		.624**	.652**
Indirect effect of agile working		.255*	.235*

* indicates $p < .05$. ** indicates $p < .01$. *** indicates $p < .001$

With regards to psychological safety, we found, in line with Hypotheses 4 and 5, positive relationships with team performance (β = .294; $p < .05$) and engagement (β = .391; $p < .05$). Finally, we found that psychological safety climate partially mediated the relationship between the agile way of working and both outcomes in accordance with Hypotheses 6 and 7. First, we found that the agile way of working is positively related to the team's psychological safety climate, which in turn, is positively related to the team's performance (β = .235; $p < .05$). Second, we also found that the agile way of working indirectly relates to the team's engagement via psychological safety climate (β = .255; $p < .05$). A summary of the main findings can be found in Figure 4.1.

Figure 4.1. Hypothesized model with results of the structural equation model



Notes: $N = 97$, *** $p < .001$; ** $p < .01$; * $p < .05$

Discussion

This study aimed to examine the effects of the agile way of working on team performance and engagement across different functional domains and to explore the mediating role of psychological safety climate in these relationships. First, as expected, our results indicate that the agile way of working is positively related to both team performance and engagement. This is in line with previous empirical studies (Melo et al., 2013; Ramirez-Mora & Oktaba, 2018; Wood et al., 2013). Furthermore, it is in accordance with the engagement and work team literature, in which it has been argued that core agile characteristics, like self-management, lead to enhanced engagement among team members (e.g. W. Schaufeli, 2012). In addition, our results support the idea that the agile way of working enhances efficient and effective team performance through simplicity, face-to-face communication, reflexivity, self-management, and quick product turnaround (e.g. Dingsøyr et al., 2016). As we included 97 teams working in different functional domains within a multinational bank, it appears that the agile way of working is indeed beneficial beyond the IT setting.

Moreover, in line with the proposition that the agile way of working promotes open, trusting, and honest communication among team members (Ramirez-Mora & Oktaba, 2018), we found that the agile way of working is positively related to psychological safety climate. In addition, following the psychological safety climate literature (Frazier et al., 2017; Newman et al., 2017), we found that psychological safety climate is positively related to team engagement and performance. Finally, in line with the input-mediator-output-input model (Ilgen et al., 2005), the results indicated that psychological safety climate partially mediates the relationship between the agile way of working and team engagement and performance. These findings may, on the one hand, help practitioners explain why the agile way of working is beneficial and, on the other hand, show researchers that psychological safety climate is an important emergent state in the context of agile teams.

In sum, our findings indicate that organizations may benefit from implementing the agile way of working in teams operating in different functional domains. Therefore, the first practical implication which emerges from our study is that the agile way of working may be used to increase team engagement and performance. The second practical implication relates to the finding that adherence to the core characteristics of the agile way of working is beneficial, since organizations may now consider focusing on these characteristics instead of the actual agile practices that are currently used in the IT setting, such as the “retrospective”, “daily stand-up” and “sprint planning”. This is relevant, as teams may struggle when focusing exclusively on the practices. For example, Hobbs and Petit (2017) found that when teams work on multiple projects and with multiple stakeholders, teams are faced with many tasks that cannot be planned upfront. Consequently, a “sprint planning” in which the tasks

for the upcoming period are planned upfront may be more difficult to create. This led teams to use agile practices selectively or not at all. However, if teams would focus on sprint planning, which is that teams self-organize their work while having a quick product turnaround, they may find that there are other, more fitting ways to adhere to the characteristics of the agile way of working. For instance, teams may find that creating a more general planning to which they add new tasks daily may help them (e.g., Kanban board). Like the "sprint planning", this allows teams to control the tasks that need to be done and at the same time adheres to the principle of a quick product turnaround, while also providing flexibility. As different contexts have their own challenges, this study thus indicates that teams may be agile about implementing and using agile practices as long as they strive for self-management, face-to-face communication, reflexivity, a quick product turnaround and simplicity.

The third practical implication is that organizations can use the agile way of working to foster a climate of psychological safety. This is important as psychological safety is related to many beneficial team outcomes (Frazier et al., 2017), but does not emerge automatically (Edmondson, 2003; Edmondson & Lei, 2014). It has been argued that this is where the agile way of working can help. Specifically, Thorgren and Caiman (2019) argue that the core characteristics of the agile way of working, like self-management and frequent communication, can cause team members to view each other like family who have a shared responsibility, and enables the creation of relationships strong enough for open, honest discussions that leave room for admitting mistakes. In the same vein, Buvik and Tkalich (2022) have argued that the self-management aspect of agile teams enables members to freely experiment and search for solutions, which can also lead to the emergence of psychological safety climate. Therefore, organizations interested in fostering a psychological safety climate may also consider implementing the agile way of working as a means to an end.

Finally, while scholars struggle to capture the concept of the agile way of working due to the many different agile practices and variations of these practices used (Hess et al., 2019), our study may also help scholars look beyond agile (management) practices and focus upon studying why (the emergent states via which) and when (the conditions under which) these core beliefs and principles behind the agile way of working may be effective. Moreover, as our study illustrated, they may do this by applying an "agile bundle" approach. Specifically, we postulated and found support for the notion that agile practices may be grouped into an overarching bundle to achieve beneficial results similar to how multiple HR practices are used to foster a high-performance workplace climate at the individual level (P. Boxall & Macky, 2009; MacDuffie, 1995).

Limitations and directions for future research

This research comes with several limitations. First, although collaboration with customers is a critical component of the agile way of working (e.g. Espinosa-Curiel et al., 2018; Gren et al., 2020), we did not include it in our study. The reason for this was twofold. On the one hand, our study focuses upon the internal dynamics of agile teams by researching psychological safety climate as a mediator, which is why we decided to exclude this more externally focused element of the agile way of working. On the other hand, we also had statistical reasons for excluding this element from the paper. Specifically, the ICC(2) value indicated that it was not appropriate to aggregate the scores of customer collaboration to the team level (i.e., all items and the scale as a whole scored below the threshold of .40; (Klein & Kozlowski, 2000). A potential reason for this may be that members have different roles within agile teams, and thus communicate with their stakeholders to various degrees. Nevertheless, as customer collaboration is considered to be crucial for the agile way of working (Beck et al., 2001), we recommend scholars look further into this dimension in the future.

Second, all survey data was collected from the same source (the team members) at a single point in time. Although our data collection method reduced the burden for participating in this research and ensured we could compare, for example, team performance in various functional domains, and a CFA model in which all items included in this research were loaded onto a single factor resulted in a poor fitting model, our research outcomes may have still been subject to common method biases (P. M. Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Although it is common within the team literature to reduce common method bias by asking team leaders to rate the team performance, we found that the absence of a strict hierarchy typical to the agile way of working (Hoda et al., 2012) and its extensive, ever-evolving, distribution of leadership roles, made it difficult to point out any role capable of rating all relevant performance aspects for agile teams for two reasons (Gronn, 2002; Mathieu et al., 2008; Spiegler, Heinecke, & Wagner, 2021). First, although there are members within the team that focus upon certain aspects of performance, like efficiency (e.g. scrum master), customer satisfaction (e.g. product owner) or experts' personal development (e.g. chapter leader), we found that these individuals rarely considered themselves to be a manager and were unwilling to fill out a "manager survey" as a result. Second, as Spiegler et al. (2021) explain, leadership within agile teams evolves and can become more distributed over time as teams become more mature. To reduce the chances of potential common method biases in the future, we therefore recommend scholars to gather data from other sources, such as the scrum board or observation of team behaviors. In order to utilize performance scores rated by others in the future, we recommend that scholars explore the different leadership roles within agile teams and consider the context of the teams when doing so. This in line with how Spiegler et al. (2021) explored the role of scrum master. Additionally, we also recommend

intervention studies in which teams' transitions to the agile way of working are observed to make causal inferences about the effects of this working method.

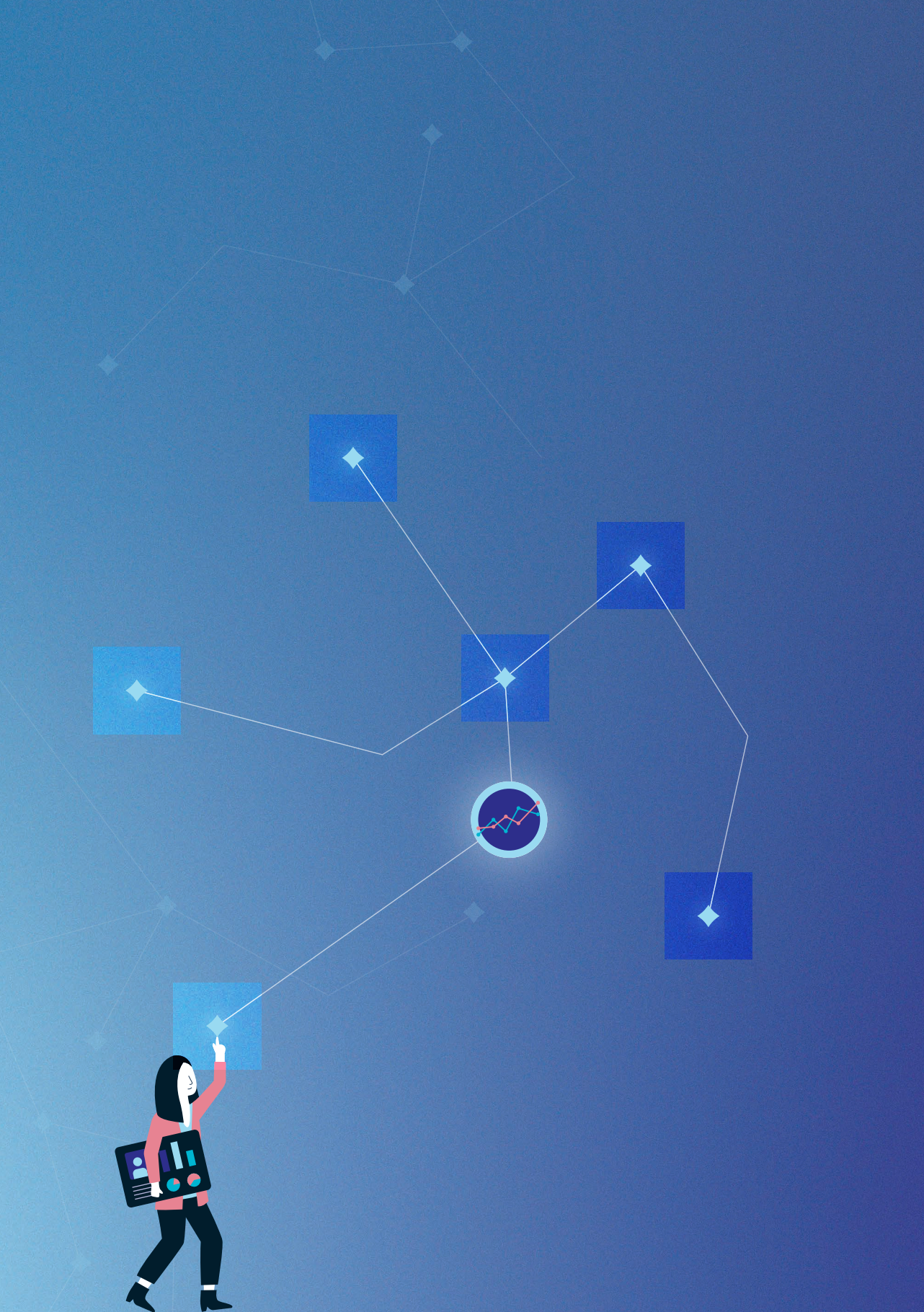
Third, following the literature on strategic human resource management (SHRM), we decided to study agile practices as a bundle. Specifically, the configural approach within SHRM proposes that when certain HR practices are combined, like for instance autonomy, information, development and rewards, more beneficial results can be achieved than one would assume based upon the sum of the individual effects (P. Boxall & Macky, 2009). Likewise, we assumed that synergetic effects may also occur among the agile practices described in the agile manifesto (Beck et al., 2001). However, similar to many SHRM scholars, we did not test whether any interactions occurred between the different agile practices (Hauff, 2021) nor did we test contrasting configurations composed of different agile practices (e.g. Verburg, Den Hartog, & Koopman, 2007). Consequently, we recommend future research to assess whether such interaction effects exists between agile practices. Moreover, regarding configurations, we recommend scholars to examine the possibility that different configurations may, for example, be desirable depending upon the context the agile team works in (e.g. retail, tech).

Finally, we recommend that future research should research the possible mediators that may explain how the agile way of working leads to beneficial team outcomes. Although our research showed psychological safety climate is an important emergent state in explaining how the agile way of working may lead to improved team performance and engagement, our mediation effects are only partial and the majority of scholars assume that the agile way of working is indirectly related to team outcomes (e.g. Melo et al., 2013; Tripp et al., 2016). Therefore, other pathways may be researched in the future, such as shared mental models and team coordination (Dingsøyr et al., 2016; Mathieu et al., 2008).

Conclusion

In this research, we showed that the agile way of working leads to improved performance and engagement via—but not exclusively—through the psychological safety climate of a team. Moreover, the agile way of working appeared to be beneficial across functional domains. This means that the increasingly widespread adaptation of the agile way of working in practice may indeed be a valid way to improve team performance and engagement for organizations.

Footnote:
Approved by the ethical review board of our university (project reference number: RP87)



5

Exploring the nature and antecedents of employee energetic well-being at work and job performance profiles

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Abstract:

While it is generally assumed that employees who feel well are also productive, research has shown that this is not always the case. Specifically, some employees seem to experience low well-being while performing, and vice versa. As employee well-being and performance are both required to achieve corporate sustainability, the purpose of this research was to identify ener-gy-related well-being/job performance profiles among 5729 employees from the Dutch division of a large bank and identify their antecedents. Using latent profile analysis, we found five profiles: 1. low well-being/low performance, 2. low well-being/medium performance, 3. high well-being/medium performance, 4. high well-being/high performance, and 5. high well-being/top performance. Using multinomial regression, we found that more learning and development opportunities, more social support from colleagues, more autonomy, and less role-conflict were related to the high well-being profiles. Second, more role clarity, more per-formance feedback, more autonomy, and less work-pressure were related to the high- and top-performance profiles. Finally, communication and social support from the manager were found to be relatively weak antecedents of the different profiles. This study thus highlights that the job demands and resources of employees may affect their well-being and performance.

Keywords: Well-being profiles; job demands; job resources; person-centered approach; sustainable work

Introduction

In pursuit of economic viability and social responsibility, a growing number of organizations are striving to simultaneously address the interests and concerns of multiple stakeholders. These companies are attempting to combine the pursuit of financial gains and social goals (protecting the environment, promoting healthy living, and ensuring employees' health and well-being) (Battilana et al., 2020). In this context, management and employees are two important internal organizational stakeholders. While the managerial perspective remains dominant in the field of strategic human resource management (SHRM), there have been recent calls to more closely consider the concerns of multiple stakeholders (Jackson et al., 2014 p. 31) by exploring how win-win situations that directly both benefit employees and management can be achieved (Beer et al., 2015; P. Boxall, 2013, 2021). Empirical studies have demonstrated that high happiness well-being (e.g., employees' satisfaction with their work) and performance can go hand-in-hand (K. Jiang et al., 2012; van de Voorde et al., 2012). Other studies, however, have shown that organizations striving to improve their performance may also increase work intensity, which (unintentionally) negatively affects employee health well-being (e.g., exhaustion) (Jackson et al., 2014; Ogbonnaya & Nielsen, 2016; van de Voorde et al., 2012). This indicates that simultaneously promoting happiness and health well-being, while stimulating job performance is a challenging endeavor for organizations. Unfortunately, employee happiness well-being has primarily been studied as means to achieve performance and health well-being in parallel with performance (Peccei & van de Voorde, 2019), and the possibility that happiness, health, and performance co-occur in complex patterns has largely been neglected in SHRM literature. Hence, prior studies have provided limited insights into how organizations can simultaneously address the interests of managers and employees by creating sustainable jobs (high levels of performance combined with high levels of happiness and health well-being) (Peccei & van de Voorde, 2019). Therefore, this article investigates how employee well-being and job performance co-occur in various combinations (reflecting different balances between management and employee interests).

Only recently have scholars begun to explore the co-occurrence of employee well-being experiences and performance behaviors at work by applying a person-centered approach. The few empirical studies following this line of enquiry have revealed that distinct types of employee well-being and employee well-being/performance profiles exist e.g., (e.g. Ayala et al., 2017; Benitez, Peccei, & Medina, 2019; Peiró et al., 2019; Tordera et al., 2020). For example, Tordera et al. (2020) found evidence for four patterns of happiness well-being and job performance, including a sustainable (happy-productive) and three unsustainable patterns (e.g., unhappy-productive). However, thus far, scholars have primarily studied job performance together with positive happiness indicators of well-being at work (e.g., life satisfaction and vigor), e.g., (e.g.

Ayala et al., 2017; Benitez et al., 2019; Peiró et al., 2019; Tordera et al., 2020), while neglecting its negative health-related indicators (e.g., emotional exhaustion), or they have studied indicators of well-being at work only (Ayala et al., 2017; Peiró et al., 2019; Tordera et al., 2020). Positive happiness well-being and negative health well-being, however, are seen as distinct, from a conceptual and empirical point of view (Benitez et al., 2019; Salanova, Del Líbano, Llorens, & Schaufeli, 2014; Somers, Birnbaum, & Casal, 2019). Moreover, some working conditions, such as large workloads, benefit positive indicators of happiness well-being (e.g., satisfaction) and job performance but are harmful for negative indicators of health well-being e.g., (e.g. LePine, Podsakoff, & LePine, 2005; N. P. Podsakoff, LePine, & LePine, 2007). Therefore, we will investigate the combination of job performance and a positive aspect of happiness well-being (vigor) and a negative indicator of health-related well-being (emotional exhaustion). There are three justifications for investigating this particular combination. First, according to W. B. Schaufeli and Bakker (2004), vigor and exhaustion can be seen as largely independent states of energetic well-being. Second, an increased proportion of employees feels exhausted at the end of the workday and less vigorous (Eurofound, 2017). Third, vigor and emotional exhaustion have profound implications for both employees (e.g., life satisfaction) and organizations (e.g., financial performance) (Campbell & Wiernik, 2015; Erdogan, Bauer, Truxillo, & Mansfield, 2012; Harter, Schmidt, & Hayes, 2002). To the best of our knowledge, scholars have not previously studied how positive and negative indicators of well-being can be combined with job performance using a person-centered approach; thus, this is our first contribution.

To better understand the energetic well-being/performance profiles, we will also answer the call of Benitez et al. (2019) to explore their antecedents. Specifically, we will investigate the role that work conditions play in shaping these well-being/performance profiles following the job demands and resources (JD-R) model of Demerouti, Bakker, Nachreiner, and Schaufeli (2001). The JD-R model assumes that an employee's job demands and resources affect their well-being and performance outcomes (Bakker & Demerouti, 2007; W. B. Schaufeli & Bakker, 2004). As many scholars have studied the effects of job demands and resources on emotional exhaustion and engagement in isolation, we will follow the W. B. Schaufeli and Taris (2014) recommendation and study the effects of two job demands and seven job resources on combinations of vigor, emotional exhaustion, and job performance. Specifically, our second contribution is therefore to investigate whether job demands and resources can serve as antecedents for our well-being/performance profiles.

In conclusion, by exploring various energy-related employee well-being and job performance combinations, this study contributes to understanding whether different employee well-being job performance profiles exist. Furthermore, by investigating the antecedents of these profiles, our study may clarify what employees need for beneficial well-being and performance outcomes. From a practical point of view, this

may help organizations to create sustainable jobs by offering the job demands and resources an employee needs, thereby creating a win-win situation for employees and management.

Energetic Well-Being and Performance Profiles

As explained in the introduction, this study will investigate job performance and feelings of vigor and emotional exhaustion. Although there are many ways to define employee job performance, we will focus in this research on its traditional form: task performance. "Task performance" refers to the proficiency with which a worker performs the tasks central to their function and includes, among other elements, the quantity and the quality of their efforts (Campbell, 1990; Koopmans et al., 2011). Second, vigor is one of the three core elements of engagement and is characterized by high levels of energy and mental resilience while working (W. B. Schaufeli, Salanova, González-Romá, & Bakker, 2002). According to W. B. Schaufeli et al. (2002), the other two core elements are dedication and absorption. Third, "emotional exhaustion" refers to feeling depleted of one's physical and emotional resources, and this is one of the three core elements of burnout (Maslach, Jackson, Leiter, Schaufeli, & Schwab, 1986). The other two core dimensions of burnout are depersonalization and diminished personal accomplishment. Similar to vigor, emotional exhaustion is related to the energetic component of well-being. As such, it has been argued in the past that vigor and exhaustion are opposite poles on the same continuum (W. B. Schaufeli et al., 2002). However, while testing their own assumption, W. B. Schaufeli et al. (2002) found that vigor and exhaustion were only weakly negatively related. In later work, W. B. Schaufeli and Bakker (2004) explained their finding, stating that, "Feeling emotionally drained from one's work 'once a week' does by no means exclude that in the same week one might feel bursting with energy," (p. 294) and concluding that, instead of being mutually exclusive, these concepts should be seen as independent states. As vigor and emotional exhaustion are both work-related energetic well-being types, while one is an indicator of positive energy-related well-being and the other of negative energy-related well-being, we believe they are well suited for this study.

A study of well-being and job performance in conjunction is a step away from the variable-centered approach that has been primarily adopted by scholars. Although the variable-centered approach is useful for distilling general patterns, Hofmans, Wille, and Schreurs (2020) argue that it is restrictive in its assumption that the research sample is homogenous. As a consequence, it assumes that employees can be categorized as (un)happy, (un)healthy, or (not) performing and ignores the possibility that employees have unique combinations of well-being experiences and job behaviors. Prior research has shown that there may be more complex combinations of well-being and performance. For example, scholars have found that some employees can be unhappy and unproductive, whereas others are happy but unproductive (Ayala et al., 2017; Tordera et al., 2020). Furthermore, focusing exclusively upon employee

well-being, others have found that different well-being indicators can be at odds with one another. Salanova et al. (2014), for example, found that employees can feel vigorous while being unhappy; and Somers et al. (2019) identified employees who felt both stressed and satisfied with their jobs. These findings are consistent with the Bakker and Oerlemans (2011) framework for subjective well-being, which indicates that different combinations of feelings of activation and pleasantness are present in four states of well-being (i.e., engagement, satisfaction, workaholism, and burnout). Finally, previous research has shown that energetic well-being and performance indicators may mutually influence one another, as employees who feel vigorous may have sufficient energy to perform well, in contrast to those who feel emotionally exhausted (Hülsheger, Lang, & Maier, 2010; W. Jiang et al., 2019).

To capture these potential combinations of job performance and positive and negative energetic well-being, a person-centered approach is needed (Hofmans et al., 2020). The person-centered approach is useful for identifying employee profiles that differ on the qualitative and quantitative levels (Marsh, Lüdtke, Trautwein, & Morin, 2009). As Meyer, Stanley, and Vandenberg (2013) explain, quantitative differences occur when employee profiles can be distinguished based upon their relative score—for example, "high well-being/high performance" and "low well-being/low performance." Qualitative differences, on the other hand, emerge as explained by Meyer et al. (2013) when the hierarchical order of the profile scores differ for certain groups, such as "low well-being/high performance" and "high well-being/low performance". There is initial empirical support for the existence for employee profiles that differ on qualitative and quantitative grounds. Applying this person-centered approach, researchers (Ayala et al., 2017; Tordera et al., 2020) have studied a number of the positive well-being indicators (e.g., satisfaction) in conjunction with job performance and found two synergetic patterns (i.e., high-high and low-low) and two antagonistic patterns (i.e., high-low and low-high).

On the basis of this line of reasoning and prior empirical work, it seems plausible that two synergetic patterns (high well-being/high performance and low well-being/low performance) and two antagonistic patterns (high well-being/low performance and low well-being/high performance) could emerge from our data. Furthermore, additional profiles in which the positive well-being indicators and negative well-being indicators are at odds with one another could also be expected (e.g., low vigor-high performance-high emotional exhaustion, high vigor-low performance-low emotional exhaustion). However, as this is, to the best of our knowledge, the first to study positive well-being indicators (vigor), negative well-being indicators, and performance (task performance) in conjunction, we make no a priori predictions about the profiles we will identify within the data or how many will emerge. This decision to make no predictions is consistent with previous research applying a person-centered approach (e.g. Bennett, Gabriel, Calderwood, Dahling, & Trougakos, 2016; Gabriel et al., 2019),

and fits the inductive nature of this approach. Therefore, our first research question is as follows:

> *Research question 1: Are there distinct employee well-being profiles (vigor and emotional exhaustion) and performance profiles that vary quantitatively (level) and qualitatively (shape)?*

Job Resources and Profiles

This section will discuss how job resources can result in different well-being/performance profiles. In the literature, four types of job resources are distinguished: resources located at the organizational level (e.g., communication), the interpersonal level (e.g., social support), the way in which the job is organized (e.g., role clarity), and the task level (e.g., autonomy) (Bakker & Demerouti, 2007). In general, the JD-R model assumes a similar path for all job resources. First, in line with effort-recovery theory (Meijman, Mulder, Drenth, Thierry, & de Wolff, 1998), it is argued that providing employees with job resources increases their external motivation to invest effort in their work. Second, in line with self-determination theory (Ryan & Deci, 2000), it is argued that employees who receive job resources become intrinsically motivated, as these resources allow them to fulfill their basic human needs for autonomy, relatedness, and competence. As a result, the "motivational path" of the JD-R model argues that job resources cause employees to feel more vigorous and achieve a higher performance (Bakker & Demerouti, 2007; W. B. Schaufeli & Taris, 2014; Xanthopoulou, Baker, Heuven, Demerouti, & Schaufeli, 2008). In addition, employees who possess more job resources have also been shown to perceive less strain, which makes them less likely to experience feelings of feeling burned out (Hobfoll & Freedy, 1993). While positive effects on well-being and performance can be expected, W. B. Schaufeli and Taris (2014) warn that the same job resources will have differential effects on outcomes. Therefore, based upon the work of Bakker and Demerouti (2007), we will include seven types of job resources in our study—namely, communication (organizational level); social support from colleagues and the manager (interpersonal level); role clarity (organization of work); and learning opportunities, autonomy, and performance feedback (task level). It can thus be assumed, at a general level, that job resources will be related to positive well-being and performance profiles. However, as their exact relationship with well-being/performance profiles has yet to be explored, our second research question is as follows:

> *Research question 2: Do job resources (at the organizational, interpersonal, organization-of-work, and task levels) differentiate employee well-being from performance profile?*

Job Demands and Profiles

This section will discuss how job demands can result in different well-being/performance profiles. In line the meta-analysis of Lee and Ashforth (1996) and the model of compensatory control (Hockey, 1997), the JD-R model assumes that job demands have a negative effect on well-being. Specifically, it is argued that, in a situation of high demand (e.g., work pressure), employees try to protect their performance by increasing their effort. Although employees can use various coping strategies to manage this (e.g., taking breaks), their energy levels become drained if their job demands are high for a prolonged period of time. As a result, the "health impairment path" of the JD-R model assumes that job demands lead to emotional exhaustion and, more generally, to burnout (W. B. Schaufeli & Bakker, 2004). Although research has consistently found that job demands lead to emotional exhaustion (W. B. Schaufeli & Taris, 2014), the proposition of the JD-R model that job demands are not directly related to engagement has been called into question. In a meta-analysis, Crawford, LePine, and Rich (2010) showed that specific job demands are positively and directly related to engagement, whereas others negatively affect this positive indicator of well-being. Consequently, they argue that there are two types of job demand: challenging demands and hindering demands. Although both types of demand lead to increased levels of emotional exhaustion, Crawford et al. (2010) found that challenging demands (e.g., work pressure) can motivate employees to perform. In line with this, challenging demands have been found to be positively related to vigor and performance (Crawford et al., 2010; LePine et al., 2005). In contrast, hindering demands (e.g., role conflict) are associated with negative emotions that make employees less willing to invest energy into dealing with them (Crawford et al., 2010). In line with this, hindering demands have been found to be negatively related to vigor and performance (Crawford et al., 2010; LePine et al., 2005; Tubre & Collins, 2000).

Based upon the previous, it can thus be assumed that challenging demands and hindering demands have different effects on task performance, vigor, and emotional exhaustion. Therefore, we have included work pressure as a challenging demand and role conflict as a hindering demand in our model, in line with prior work (Bakker & Demerouti, 2007; Humphrey, Nahrgang, & Morgeson, 2007). As few scholars have explored the relationships between job demands and performance, vigor, and emotional exhaustion together—much less in conjunction—our final research question is as follows:

> *Research question 3: Do job demands (challenging and hindering) relate to different employee well-being and performance profiles?*

Materials and Methods

Sample and procedure

For this research, a pre-existing dataset was taken from a large multinational company operating in the financial sector. The company originated through a series of mergers in the Netherlands, after which it expanded throughout the world. As of today, it is among the largest 30 banks worldwide and has its head office within the Netherlands. To offer a work environment that enhances well-being and enables employees to perform at their best, the company collaborates with a consultancy agency to improve the vitality of its workforce through 1. a self-assessment report for individual employees that provides insights into its workers' job demands, resources, and well-being, while offering tips and tricks for improvement; and 2. departmental- and organizational-level reports, with insights for management into workers' job demands, resources, and well-being. To generate these reports, surveys were distributed by the consultancy firm to all employees working in the Netherlands (N = 18,230) in June 2020. In total, 8839 (31%) people filled out the survey.

Due to the sensitive topics assessed in this survey (e.g., work pressure), the survey included no demographic questions. For similar reasons, we only had access to the fully anonymized data set, which means that we cannot discuss the specific characteristics of our sample. Instead, we will describe the characteristics of the entire population working for this organization in the Netherlands. This population consists of those working for the head office (n = 8413) and the Dutch division of the bank (n = 9817). There were similar response rates for the head office workers (28%) and Dutch division workers (33%). In this population, 64% of the workers are male and 36% are female. In addition, 2.31% are aged under 25 years, 29% are 26–35 years, 28.4% are 36–45 years, 26.7% are 46–55 years and 13.7% are older than 56 years. Finally, 85.5% of the employees have Dutch nationality. As the entire population was involved in this research, the functional areas included ranged from sales agents up to the CEO of the organization.

Finally, as we made use of a pre-existing dataset, we requested and acquired the approval of our university's ethical review board after the dataset had been acquired. Similarly, the data privacy officer of the organization granted us permission to use this data for academic research after the primary purpose had been completed (e.g., providing self-assessment reports to employees and departments and organizational reports to managers).

Measures

The survey offered by the consultancy firm was the "JD-R monitor." This survey is a commercialized online survey, developed based upon the JD-R model (W. B. Schaufeli & Taris, 2014), in collaboration with Prof. Dr. Wilmar Schaufeli, a leading scholar in this

area. All rights to the items and scales are reserved by the consultancy agency. To assess the reliability and validity of the antecedents of the well-being/performance items, we conducted a confirmatory factor analysis (CFA) and reliability analysis. The CFA was conducted using the package Lavaan (v.06-8) and the reliability analysis used the Psych package (v2.1.3) in R. Like other researchers (Brauner, Wöhrmann, Frank, & Michel, 2019; Magidson, Vermunt, & Madura, 2020; Van Den Groenendaal, Rossetti, Van Den Bergh, Kooij, & Poell, 2021), we conducted a latent class analysis (LCA) on the item level to identify the well-being and performance profiles. We did not conduct these analyses for the included well-being and performance items.

Job resources: In total, seven job resources were included in this research. These resources can be subdivided in four categories, according to Bakker and Demerouti (2007): resources stemming from the organization at large, the way in which the work is organized, interpersonal resources, and task resources. All resources were measured using three items each. First, communication was included as a job resource at the organizational level. For example, *"I am sufficiently informed about developments within my organization."* The answer scale for both variables ranged from "totally disagree" (1) to "totally agree" (5), and it appeared to be sufficiently reliable ($\alpha = 0.68$). Second, one type of resource concerned the way in which the work was organized ("role clarity"). One example item is, *"Do you know exactly what is expected of you at work?"* Answers were given using a Likert-scale, ranging from "never" (1) to "always" (5). The scale was found to be reliable ($\alpha = 0.80$). Third, two types of resources associated with the interpersonal level were included—namely, social support from colleagues and from (line) management. An example of an item for colleague support is, *"Can you count on your colleagues for help and support, when needed?"*, and an example for management support is, *"Can you count on your line manager for help and support when needed?"*. The answer scales ranged from "never" (1) to "always" (5) and the reliability of colleague support ($\alpha = 0.76$) and manager support ($\alpha = 0.87$) appeared to be sufficient. Fourth and finally, three types of task-level resources were included: learning opportunities, autonomy, and performance feedback. An example of the learning opportunities scale is, "*My job offers adequate opportunities for personal growth and development.*" Second, *"Can you determine the content of your work?"* is an example from the autonomy scale. Third, for performance feedback, an example item is, *"Does your line manager provide information about how well you do your job?"*. The respondents were, again, invited to answer on a scale ranging from "never" (1) to "always" (5). The Cronbach alpha's of the learning opportunities ($\alpha = 0.86$), autonomy ($\alpha = 0.80$), and feedback ($\alpha = 0.76$) scales indicated that they were reliable.

Furthermore, two CFAs were conducted simultaneously for the seven job resources. First, a unidimensional model was tested to verify whether the different dimensions should indeed be treated as separate types of resource. The model fit indicators,

specifically the chi-square (χ^2), comparative fit index (CFI), root mean square error of approximation (RMSEA) and standardized root mean square residual (SRMR), indicated that the unidimensional model was a poor fit for the data (χ^2 = 23,856 (189), *CFI* = 0.550, *RMSEA* = 0.148, *SRMR* = 0.107). In contrast, the hypothesized model consisting of seven dimensions did result in a sufficient model fit (χ^2 = 3688 [168], *CFI* = 0.933, *RMSEA* = 0.060, *SRMR* = 0.038). Therefore, all seven job resources were included as separate variables in the sequential analyses.

Job demands: For this research, two job demands were included from two subcategories. Specifically, we included the hindering-demand role conflict and the challenging-demand work pressure (LePine et al., 2005). Both job demands were measured with three items, using a Likert scale ranging from "never" (1) to "always" (5). Role conflict was measured with items such as, *"Do you have to do things at work that you would prefer to do differently?"* and work pressure with items such as, *"Do you have too much work to do?"*. The scales for role conflict (α = 0.76) work pressure (α = 0.80) appeared to be reliable. Again, we conducted a series of CFA for the items. First, the unidimensional model was tested again, with all the items of both demands loaded onto one factor. As this model indicated a poor fit (χ^2 = 3587 [9], *CFI* = 0.660, *RMSEA* = 0.263, *SRMR* = 0.156), the hypothesized model with the two separate demands was tested instead. This model appeared to fit the data (χ^2 = 144 [8], *CFI* = 0.987, *RMSEA* = 0.055, *SRMR* = 0.032). Consequently, role conflict and work pressure were included in the sequential analyses.

Well-being: As explained before, both positive and negative facets of well-being were included in this research. We included two items for each facet, and respondents answered on a Likert-point scale ranging from "never" (1) to "always" (5). Vigor was included using two items from the Utrecht work engagement scale (W. B. Schaufeli et al., 2006), and an example is, *"At work, I am bursting with energy."* Emotional exhaustion was included using two items from the Utrecht burnout scale of W. B. Schaufeli and Van Dierendonck (2000), and an example is, *"I feel burned out at work."*

Performance: For performance, we included three items that used an 11-point Likert-scale ranging from "totally dissatisfied" (1) to "totally satisfied" (11). An example of an item is, *"How would you rate the quality of your work in the past four weeks?"*.

Finally, we investigated the correlations between the well-being and performance items. This analysis showed that the two items on similar topics (i.e., vigor, emotional exhaustion, or performance) had correlations ranging from 0.54 to 0.71. Between the topics, the correlations between the items ranged between −0.41 and 0.32. Therefore, it is concluded that neither the items nor their topics were redundant and different profiles may appear when conducting an LCA on these seven items.

Analyses

To identify the relevant employee well-being/performance profiles, we used LCA. At its core, LCA assesses whether the parameters of a statistical model vary for different unobserved subgroups (Vermunt & Magidson, 2004). This means that LCA can be used to identify typical response patterns for specific questions and identify sub-groups within the dataset. As such, it is typically used as an inductive approach when the number of classes is not known beforehand (Bennett et al., 2016). To determine the optimal number of profiles, the resulting models are compared based upon their model fit, specifically the Akaike information criterion (AIC), Bayesian information criterion (BIC), chi-square (χ^2) and the G-square ($G^{2)}$), and the primary goal is to select a fitting model with the lowest number of classes (Magidson et al., 2020). For the model fit indicators used in this study, lower values indicate better performing models. Aside from statistical criteria, the model should also be evaluated for its theoretical and empirical interpretability. In line with Magidson et al. (2020), we ran the LCA on the item scores to identify meaningful response patterns in the data. For this purpose, we used the package PoLCA (v1.4.1) in R. The parameters were estimated using the maximum likelihood method, with 1000 iterations to identify different profiles within the data based upon a pre-set number of classes. Rerunning the analyses with different numbers of classes allowed us to identify the most suitable number of well-being and performance profiles. Sequentially, we labeled the clusters by investigating their response patterns on the items measuring vigor, exhaustion, and performance, and we assigned each respondent to their predicted class using the PoLCA package. A new categorical variable was thus created for each respondent to indicate their class membership. To verify the profiles, various analyses of variance (ANOVAs) and Tukey's multiple comparison tests were performed to assess whether the mean scores of the vigor, exhaustion, and performance items varied significantly between the profiles.

To assess which antecedents are predictive of the resulting profiles, we conducted a multinomial regression analysis using the package Nnet (v.7.3-16). This analysis compared the likelihood of an employee being a member of a certain profile with a referent group based on a specific antecedent. To facilitate the interpretation of the results, the odds ratio (*OR*) was calculated. The coefficients were transformed into an *OR* by taking the exponential of the coefficients. The *OR* reflects "the change in likelihood of membership in a target profile versus a comparison profile associated for each unit of increase in the predictor" (Morin, Meyer, Creusier, & Biétry, 2016, p. 246). Thus, an *OR* of 2 suggests that, with each unit-increase of a specific job demand or resource, the likelihood of being a member of a specific profile is two times higher than that of the referent profile. An *OR* under 1, for example .50, suggests that the likelihood of profile membership is reduced by 50% in comparison to the referent profile (Morin et al., 2016). Finally, it should be noted that, as in other LCA studies (e.g., [14,36,37]), no additional control variables were used in this analysis.

Results

Descriptives

Table 5.1 shows the means, standard deviations, correlations, and Cronbach alphas of the job demands and resources. As can be seen from this table, all job resources correlated positively with one another and were typically negatively correlated with the job demands. The exception to this were the correlations of work pressure with learning and development ($r = 0.03$, $p < 0.05$) and performance feedback ($r = 0.05$, $p < 0.01$). Similarly, role conflict and work pressure appeared to be positively related with one another ($r = 0.30$, $p < 0.01$).

Well-Being and Performance Profiles

As mentioned in the methods section, the number of classes was determined by an inductive approach in which the number of classes was increased until the most statistically and theoretically suitable model had been found. The pre-determined number was increased until the fit measures—such as the BIC and AIC—no longer indicated a model improvement or until the model no longer converged. In Table 5.2, the model fit indicators are presented for LCA solutions up to six classes. For seven classes, the model no longer converged. As can be seen from the model, fit indices such as the BIC and AIC favor the most complicated, six-class model, as both values are at their lowest point for this solution. However, the difference in fit indices with the five-class model is relatively small, and the six-class model often failed to replicate the solution. Moreover, in the six-class solution, a profile consisting of a very small sub-set (4.36% of the sample) was created and the solution appeared to be more difficult to interpret than the five-class solution. Therefore, the five-class solution was chosen as it statistically outperformed the other solutions and provided the most meaningful solution from both the theoretical and the empirical perspectives.

Table 5.2: Summary LCA for different models

	2 classes	3 classes	4 classes	5 classes	6 classes
ML	-55,120	-53,350	-52,352	-51,659	-51,162
P	93	140	187	234	281
χ^2	945,706,587	363,021,769	33,287,984	23,041,505	23,251,183
BIC	111,045	107,912	106,322	105,344	104,793
AIC	110,426	106,981	105,078	103,787	102,923
G^2	27,040	23,501	21,504	20,119	19,125

Note. Abbreviations used are as follows: maximum likelihood (ML), parameters (P), chi-square (χ^2), Akaike information criterion (AIC), Bayesian information criterion (BIC), chi-square ($\chi 2$) and the G-square (AIC, BIC, $\chi 2$, and (G2).

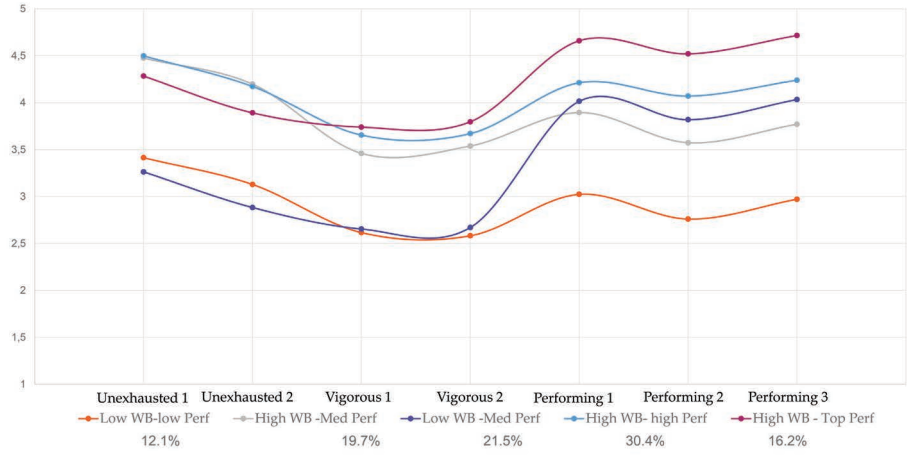
Table 5.1: Correlations and descriptives of the antecedents.

	M	SD	1	2	3	4	5	6	7	8	9
1. Learning opportunities	3.69	0.79	(.86)								
2. Communication	3.42	0.67	.42**	(.68)							
3. Role clarity	3.71	0.75	.23**	.36**	(.80)						
4. Colleagues social support	3.86	0.73	.35**	.35**	.34**	(.76)					
5. Manager social support	3.89	0.92	.37**	.46**	.35**	.47**	(.87)				
6. Feedback	3.07	0.78	.33**	.42**	.36**	.47**	.54**	(.76)			
7. Autonomy	3.45	0.84	.33**	.27**	.09**	.21**	.23**	.23**	(.80)		
8. Work pressure	3.31	0.86	.03*	-.08**	-.04**	-.06**	-.08**	.05**	-.03**	(.80)	
9. Role conflict	2.17	0.74	-.23**	-.34**	-.29**	-.23**	-.23**	-.09**	-.08**	.30**	(.76)

Note. M and SD represent mean and standard deviation, respectively. The Cronbach's alpha is displayed on the diagonal. Values range from 1–5 for all variables, for which 1 is the lowest score and 5 is the highest. * indicates $p < 0.05$. ** indicates $p < 0.01$.

The five-class solution is shown in Figure 5.1. As shown there, the first class (12.1%) has low scores for all well-being and performance items (orange line). Therefore, we labeled this the "low well-being/low performance" profile. The second class (19.7%) scored relatively highly on the well-being items, but it had the second-to-lowest performance pattern of all profiles (gray line). This profile was sequentially labeled the "high well-being/medium performance" profile. The third class (21.5%) is characterized by its low scores on the well-being items, but it scored mid-range for performance (blue line). Therefore, we labeled this class the "low well-being/medium performance" profile. The fourth class (30.4%) scored highly on all well-being and performance profiles (blue line) and therefore received the label of the "high well-being/high performance" profile. Finally, the fifth group (16.2%) also scored highly on all well-being items, but it had a distinctively high-performance pattern (purple line). Therefore, we labeled this class the "high well-being/top performance" profile.

Figure 5.1. Profile plot five-class solution. To facilitate the interpretation of this figure, the items from "emotional exhaustion" were mirrored, so that higher scores indicate increased levels of well-being. Moreover, the performance scale ranging from 1–11 was transformed to a five-point scale.



We conducted ANOVAs to test whether the profiles that we found were distinctive. A Tukey's mean score comparison test was conducted where the ANOVA results indicated that the mean scores differed significantly from one another. These analyses showed that the means of the first vigor item (*Mdiff* = 0.037, *p* = 0.851) and the second vigor item (*Mdiff* = 0.089, *p* = 0.067) were not significantly different for the "low well-being/medium performance" profile and the "low well-being/low performance" profile. Additionally, we found that, for the "high well-being/medium performance" profile and the "high well-being/high performance" profile, the means of the first (*Mdiff* = −0.024, *p* = 0.914) and second exhaustion items (*Mdiff* = 0.0252, *p* = 0.917) were not significantly different. As all other mean scores for vigor, exhaustion,

and performance were found to be significantly different across the five profiles, it is concluded that it is indeed possible to distinguish five unique well-being and performance profiles, as identified in the LCA.

Finally, it should be noted that the profiles we found differed in qualitative and quantitative terms. In terms of quantitative differences, we found three profiles that differ in their levels of all vigor, exhaustion, and performance items (i.e., the "low well-being/low performance," "high well-being/high performance," and "high well-being-top performance" profiles). In addition, we found two qualitative different profiles. One combined low levels of well-being with medium levels of performance (i.e., the "low well-being/medium performance" profile) and the other combined high levels of well-being with medium levels of performance (i.e., "high well-being/medium performance" profile). Therefore, the results confirm the value of using the person-centered LCA method (Meyer et al., 2013).

Test of Antecedents

To answer our second and third research questions, we investigated whether job demands and resources were differentiated for the five profiles that we found. Specifically, we used multinomial regression to test whether seven job resources (communication, role clarity, social support from colleagues, social support from managers, learning opportunities, autonomy, and performance feedback) and two job demands (work pressure and role clarity) determined profile membership. The results of this analysis can be found in Table 5.3.

Organizational-level resources: Communication appeared to do relatively little to distinguish our profiles, with two exceptions. First, employees who perceive higher levels of communication were 1.3 to 1.5 times less likely to be in the "low well-being/low performance" profile compared to the other profiles. Second, communication increased the likelihood of membership in the "high well-being/high performance" profile relative to "high well-being/medium performance" (*OR* = 1.22).

Organization of work: Having more role clarity appeared to increase the likelihood of being in the high- or top-performance profile, in comparison with the low-to-medium performance profiles. Especially noticeable in this regard was that more role clarity made individuals 2.6 times more likely to be in the "high well-being/top performance" profile than in the "low well-being/low performance" profile. Furthermore, compared with the "low well-being/low performance" profile, greater role clarity increased the likelihood of being in one of the two medium performance profiles ("high well-being/medium performance" [*OR* = 1.36] and "low well-being/medium performance" [*OR* = 1.26]). Finally, for the two high-performance profiles, greater role clarity increased the likelihood of being in the "high well-being/top performance" profile, compared to the "high well-being/high performance" profile

(OR = 1.52). This means that, of all the profiles, employees with high levels of role clarity were most likely to fall into the "high well-being/top performance" profile.

Interpersonal resources: Social support from the managers rarely appeared to be predictive of class membership. The only exception was where this appeared to differentiate between the "low well-being/medium performance" profile and two other profiles. First, the likelihood of being in the "low well-being/low performance" profile decreased by.82 for employees with higher levels of social support from their manager in comparison to the "low well-being/medium performance" profile. Second, employees with more social support from their manager were more likely to be in the "high well-being/top performance" profile, compared to the "low well-being/medium performance" profile.

Having social support from one's colleagues appeared to be an important antecedent of the profiles, as employees with more social support from their colleagues were more likely to be a member of the high well-being profiles than the low well-being profiles. Specifically, the *OR*s of the high well-being profiles ranged between 1.34 and 1.39 in comparison to the low well-being profiles. When the two low well-being and three high well-being profiles are viewed independently, social support from colleagues appears to do little to differentiate between them.

Task resources: Learning opportunities, performance feedback, and autonomy appeared to be important antecedents of our profiles. First, having more learning and development opportunities increased the likelihood of an employee being in one of the three high well-being profiles, in comparison with the low well-being profiles. Specifically, the *OR*s of the high well-being profiles ranged between 1.67 and 1.90, in comparison to the "low well-being" profiles. When the two "low well-being" and three "high well-being" profiles are viewed separately, only two differences are observed. One, compared to the "low well-being/low performance" profile, employees with high learning and development opportunities were more likely to be in the "low well-being/medium performance" profile (OR = 1.17). Two, employees with higher levels of learning and development opportunities were 1.16 times more likely to be in the "high well-being/high performance" profile than in the "high well-being/medium performance" profile.

Table 5.3. Results of the multinomial regression

	Low WB-Low Perf vs. High WB-Med Perf		Low WB-Low Perf vs. Low WB-Med Perf		Low WB-Low Perf vs. High WB-High Perf		Low WB-Low Perf vs. High WB-Top Perf		High WB-Med Perf vs. Low WB-Med Perf		High WB-Med Perf vs. High WB-High Perf		High WB-Med Perf vs. High WB-Top Perf		Low WB-Med Perf vs. High WB-High Perf		Low WB-Med Perf vs. High WB-Top Perf		High WB-High Perf vs. High WB-Top Perf	
	Coef.	**OR**	**Coef.**	**OR**	**Coef.**	**OR**	**Coef.**	**OR**	**Coef.**	**OR**	**Coef.**	**OR**	**Coef.**	**OR**	**Coef.**	**OR**	**Coef.**	**OR**	**Coef.**	**OR**
Communication	0.23 **	1.26	0.27 **	1.31	0.42 **	1.52	0.39 **	1.48	0.05	1.05	0.20 *	1.22	0.17	1.18	0.15	1.16	0.12	1.13	−0.03	0.97
Role clarity	0.31 **	1.36	0.23 **	1.26	0.54 **	1.72	0.96 **	2.60	−0.08	0.92	0.23 **	1.25	0.64 **	1.90	0.31 **	1.36	0.73 **	2.07	0.42 **	1.52
Social support (colleagues)	0.31 **	1.36	−0.02	0.98	0.31 **	1.36	0.29 **	1.34	−0.33 **	0.72	0.00	1.00	−0.02	0.98	0.33 **	1.39	0.31 **	1.37	−0.02	0.98
Social support (manager)	−0.09	0.91	−0.20 **	0.82	−0.10	0.91	−0.04	0.96	−0.11	0.89	−0.01	0.99	0.05	1.05	0.10	1.11	0.16 *	1.18	0.06	1.06
Learning opportunities	0.52 **	1.68	0.16 **	1.17	0.67 **	1.95	0.64 **	1.90	−0.36 **	0.70	0.15 **	1.16	0.13	1.13	0.51 **	1.67	0.49 **	1.63	−0.03	0.97
Performance feedback	0.11	1.12	0.09	1.10	0.24 **	1.27	0.45 **	1.57	−0.02	0.98	0.12	1.13	0.33 **	1.40	0.14 *	1.15	0.35 **	1.42	0.21 **	1.24
Autonomy	0.17 *	1.19	−0.05	0.95	0.23 **	1.26	0.32 **	1.39	−0.22 **	0.80	0.06 **	1.06	0.15 **	1.17	0.28 **	1.33	0.37 **	1.45	0.09	1.10
Work pressure	−0.13 *	0.88	0.39 **	1.47	0.12	1.12	0.36 **	1.44	0.51 **	1.67	0.24 **	1.28	0.49 **	1.63	−0.27 **	0.76	−0.02	0.98	0.25 **	1.28
Role conflict	−0.69 **	0.50	−0.06	0.94	−0.79 **	0.45	−0.48 **	0.62	0.63 **	1.87	−0.10	0.90	0.21 *	1.23	−0.73 **	0.48	−0.42 **	0.66	0.31 **	1.36

Note: Table shows the regression coefficient and odds ratio, * = $p < .05$, ** = $p < .01$, *** = $p < .001$

Second, it appeared that employees with higher levels of performance feedback were more likely to be among the two high-to-top performance profiles than the three low-to-medium performance profiles. For example, these employees were 1.57 times more likely to be a member of the "high well-being/top performance" profile than the "low well-being/low performance" profile. Furthermore, although having more performance feedback did not appear to differentiate the three low-to-medium performance profiles, it did increase the likelihood of being in the "high well-being/top performance" profile, compared to the "high well-being/top performance" profile (OR = 1.24).

Third, having a high degree of autonomy appeared to increase the chances of being in the three high well-being profiles. Specifically, compared to the two low well-being profiles, the *OR* of being in one of the three high well-being profiles ranged from 1.19 to 1.45. Furthermore, having higher autonomy increased the likelihood of being in the high- or top-performance profile, compared to the low or medium performance. Specifically, the *OR*s of the high-performance profiles ranged between 1.06 and 1.45 in comparison to the low-to-medium performance profiles. However, while more autonomy increased the likelihood of being in the "high well-being/high performance" profile, compared to "high well-being/medium performance," this was only by a small degree (OR = 1.06).

Conclusion on job resources: In conclusion, it appears that job resources have distinct effects on well-being and performance profiles. In general, employees with more learning opportunities, social support from their colleagues, and autonomy are more likely to fall into the three high well-being profiles than the two low well-being profiles. Furthermore, employees with more role clarity, performance feedback, and autonomy are more likely to be in the two profiles characterized by high performance than in the three medium-to-low performance profiles. Finally, although there were some differences between the profiles, communication and social support from the manager did little to differentiate between the profiles. However, employees who scored highly for communication had a lower chance of being in the "low well-being/low performance" profile than in any of the other profiles.

Challenging demands: Work pressure appeared to be an important differentiator for the profiles. Most notable was that greater work-pressure made employees 1.28 to 1.67 times less likely to be in the "high well-being/medium performance" profile. Furthermore, having more work-pressure made employees more likely to be in the "low well-being/medium performance" profile than in the "low well-being/low performance" profile (OR = 1.47). Additionally, exposure to high work-pressure decreased the likelihood of being in the "high well-being/high performance" profile, in comparison with the "low well-being/medium performance" profile (OR = 0.76). Finally, high work-pressure increased the likelihood of being in the "high well-being/

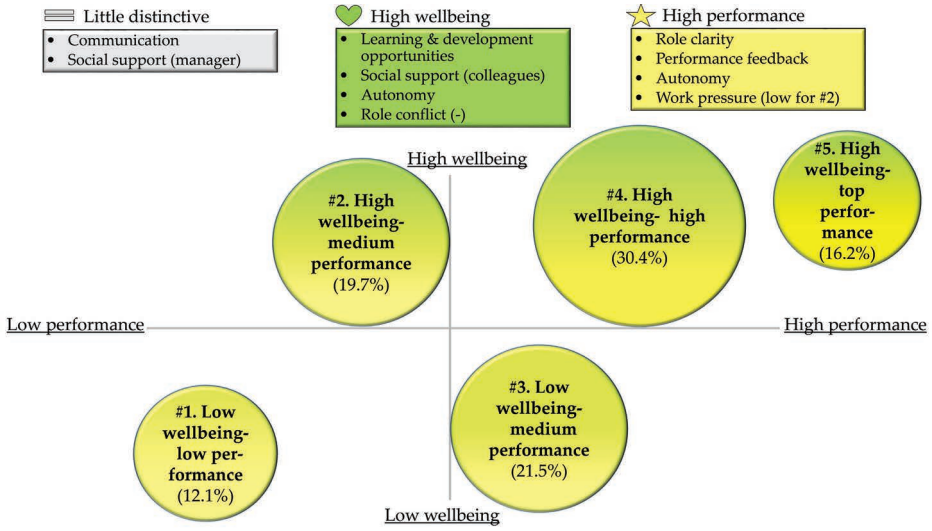
top performance" profile, compared to the "low well-being/low performance" (OR = 1.44) and the "high well-being/high performance" profiles (OR = 1.28).

Hindering demands: Generally, it appeared that perceptions of high role-conflict decreased the likelihood of being in one of the three high well-being profiles, in comparison with the two low well-being profiles. Specifically, the *OR* of being in one of the three high well-being profiles—compared to the two low well-being profiles—ranged from.45 to.66. Most notable was that, for individuals with high levels of role conflict, the chances of being in the "high well-being/high performance" profile decreased by 55%. However, higher levels of role conflict increased the chances of an employee to be in the "high well-being/top performance," in comparison with the other two well-being profiles. Specifically, role conflict increased the likelihood of being in the "high well-being/top performance" profile by 1.23, compared with the "high well-being/medium performance" profile, and by 1.36 compared with the "high well-being/high performance" profile.

Conclusion of job demands: Lower levels of work pressure increased the likelihood of an employee being a member of the "high well-being/low performance" profile. Furthermore, while differences between specific profiles were found, it appeared that greater work pressure was generally associated with the two higher well-being and (top) performance profiles. With regards to role conflict, it was found that employees with less role-conflict have a higher likelihood of having one of the three high well-being profiles in comparison to the two low well-being profiles. Surprisingly, when the three high well-being profiles are viewed in turn, it seems that having greater role conflict increases the chances of being in the "high well-being/top performance" profile.

The primary results of the analyses are also summarized in Figure 5.2.

Figure 5.2. Summary of the results.



Discussion

The aim of this study was to increase our understanding of how organizations can create jobs that are sustainable from the perspectives of both employee well-being and job performance. To do so, we first used LCA to identify well-being and performance profiles. Five energy-related employee well-being and job performance profiles emerged from the data. These profiles differed on quantitative and qualitative grounds. Specifically, we found three profiles that differed quantitatively (1. low well-being/low performance, 2. high well-being/high performance, and 3. high well-being/top performance) and two profiles that differed qualitatively (4. low well-being/medium performance and 5. high well-being/medium performance). As each profile consisted of a substantial proportion of our sample (between 12.1% and 30.4%), these outcomes support the existence of relevant and theoretically meaningful energy-related employee well-being/performance profiles.

Second, we explored whether two job demands and seven resources predicted well-being/performance profile membership. Most notably, having more learning opportunities, autonomy, and social support from colleagues and less role-conflict increased the likelihood of an employee being in one of the three high well-being profiles. Having more role clarity, performance feedback, and autonomy each increased the chances of being a member of the high- or top-performance profiles. Furthermore, employees with low work-pressure were typically in the "high well-being/medium performance" profile, while employees who perceived little communication had a higher likelihood of being in the "low well-being/low performance" profile than in

the other profiles. In general, though, communication and social support from the manager did little to differentiate our profiles. In sum, these findings indicate that job demands and resources relate differently to employee well-being/performance profiles.

Although to the best of our knowledge, this is the first study of job performance and positive (vigor) and negative (exhaustion) energetic well-being indicators, the profiles that we found are mostly consistent with previous findings on performance/well-being at work profiles. While focusing upon performance in combination with positive well-being indicators, other researchers have similarly found low well-being/low performance and high well-being/high performance profiles together with low well-being/high performance and high well-being/low performance profiles (Ayala et al., 2017; Tordera et al., 2020). In contrast to those results, our findings indicate that there may be an additional fifth profile for employees who show superior job performance over the high/high profiles. This "high well-being/top performance" profile consisted of a substantial part of our sample (16.2%). In addition, while our findings do not suggest qualitative differences between the positive and negative well-being indicators, other scholars who have focused exclusively on well-being profiles have found qualitative different patterns (Salanova et al., 2014; Somers et al., 2019). For example, Salanova et al. (2014) note that, aside from high well-being and low well-being profiles, employees who have high energy while working but derive no pleasure from it (e.g., workaholics) also exist. In contrast, a recent study by Benitez et al. (2019) only found quantitative differences between positive and negative well-being indicators (e.g., low/low and high/high profiles). Although vigor and emotional exhaustion were not found to be highly correlated, in line with W. B. Schaufeli et al. (2002), this does call into question the benefits of including multiple well-being indicators in a study of well-being/performance profiles. As we only included energetic well-being indicators in our model, future research is needed to consider other types of well-being (e.g., stress, meaningfulness) and determine whether the inclusion of different well-being indicators helps to identify profiles from a qualitative perspective.

Turning to the antecedents of these five profiles, the first point to note is the general pattern that those employees with more resources and fewer hindering demands and more work-pressure are more likely to be in the "high well-being/high performance" and "high well-being/top performance" profiles, compared to the three low well-being and low-to-medium performance profiles. This finding is consistent with the JD-R's "motivational path," which argues that job resources increase employee well-being and performance (Bakker & Demerouti, 2007; W. B. Schaufeli & Taris, 2014; Xanthopoulou et al., 2008). Our findings are also in line with the Crawford et al. (2010) distinction between challenging demands and hindering demands. Specifically, these authors argue that challenging demands—such as work pressure—enhance

employee well-being and performance, whereas hindering demands—such as role conflict—decrease well-being and performance, in line with the "health impairment path" of the JD-R model (Crawford et al., 2010; W. B. Schaufeli & Bakker, 2004).

Second, employees in the high well-being/top performance profile appear to have more role clarity, performance feedback, work pressure, and role conflict, in comparison with employees in the "high well-being/high performance" profile (30.4%). While it is consistent with the literature that a higher level of job resources and work pressure can lead to more favorable performance outcomes (Crawford et al., 2010; W. B. Schaufeli & Bakker, 2004), it is surprising that those with more role conflict are also more likely to be in the top performance profile. However, as employees within the top-performance profile also had more role clarity, it may be that role conflict is considered to be inherent to their job and is, therefore, not seen as a negative, as is normally the case for hindering demands, according to Crawford et al. (2010). Consequently, employees who expect role conflict due to their role clarity may have their expectations fulfilled by perceiving role conflict in practice, which would be in line with the finding of Ayala et al. (2017) that happy-productive employees perceive their psychological contract to be fulfilled, whereas unhappy-unproductive employees do not. Consequently, future research could investigate by whom role conflict is perceived as a hindering demand and by whom as challenging demand.

Third, a closer look at the different qualitative profiles suggests two possible explanations for membership of the "low well-being/medium performance" profile. Specifically, compared to the "low well-being/low performance" profile, employees in the "low well-being/medium performance" profile appeared to have more learning opportunities, communication, role clarity, and work pressure and less support from their managers. On one hand, and in line with the JD-R model, it may thus be argued that because these specific resources primarily relate to the task level and there is higher work pressure, employees may be more enabled and motivated to perform (Bakker & Demerouti, 2007; Crawford et al., 2010). On the other hand, as relationship with one's supervisor has appeared to be related to well-being (D. T. Hooper & Martin, 2008), it may be that the relatively low social support from the manager for this group—compared to the levels of the "low well-being/low performance" and "high well-being/medium performance" profiles—may lead to its low well-being. Alternatively, the manager may be more likely to provide social support to employees who have lower well-being scores when they also have lower job performance.

Finally, for the other qualitatively different profile ("high well-being/medium performance"), it appeared that having more work-pressure increased the likelihood of being in the "high well-being/high performance" and "high well-being/top performance" profiles, compared to "high well-being/medium performance." This is consistent with the notion of Crawford et al. (2010) that challenging demands can

be motivating. Furthermore, this finding may hint at the existence of the boosting effect described on a few occasions in the literature (Bakker, Hakanen, Demerouti, & Xanthopoulou, 2007). The boosting effect suggests that the positive effects of job resources on engagement can be strengthened by certain job demands (W. B. Schaufeli & Taris, 2014), such as work pressure. This is conceptually different from the buffering effect, which suggests that job resources may compensate for high job demands (Bakker et al., 2007). As interaction effects between job demands and resources have only been found on a few occasions (Bakker & Demerouti, 2007), more research is required to explore whether such interactions may predict employee well-being/performance profile membership.

Limitations and Directions for Future research

Several limitations for our research should be considered. First, due to data privacy and ethical considerations, we only had access to an anonymous dataset, comprising survey data gathered at one point in time. This means that we were unable to enrich our data with data from other sources such as the supervisor or human resources (HR) system. Therefore, our outcomes may have been subject to common method bias (P. M. Podsakoff et al., 2003). To reduce the potential for this issue in the future, we recommend that researchers combine data sources. For instance, performance ratings from the manager and other well-being indicators, such as absenteeism data, could be included in the LCA. Furthermore, to assess whether job demands and resources lead to certain profiles—or if it is the other way around—and to investigate the dynamic nature of these profiles in more detail, we recommend longitudinal (intervention) studies.

Second, the research was conducted with a single company (albeit a large one) that operates at the national and international levels, and it included a sample of all staff, from low-ranking up to high-ranking workers in a variety of functions (such as sales, accounting, compliance, stockbroking, and HR), each based in the company's Dutch division or head office. This one company provides an example of the possibilities of using LCA to distinguish the different profiles/categories of staff with respect to the balance or imbalance between well-being and performance and related job resources and demands. Owing to the increasing availability of survey-based data in large companies (Levenson & Fink, 2017), other firms could conduct similar analyses to discern the profiles found in their own organizations and make improvements to the mixes of available resources and challenging demands.

Third, in this research, no interaction effects between job demands and resources were used to predict membership of the well-being and performance profiles. We made this choice because of the limited empirical evidence (Bakker & Demerouti, 2007) and theoretical consensus on these effects. For instance, whereas the JD-R model has traditionally only focused on buffering effects in which job resources can

compensate for high demands, boosting effects have recently been introduced to explain how job demands can strengthen the positive effects of job resources (Bakker & Demerouti, 2017). Furthermore, although some researchers have suggested that job resources should be matched to job demands to find significant interaction effects, others have shown that job demands and resources that have conceptually little in common are able to boost engagement (Bakker et al., 2007). Considering that well-being and performance profiles are relatively underexplored, we made the choice not to further complicate our research by also investigating these interactions. Nevertheless, some of our findings do hint to the existence of interaction effects, such as the "high well-being/top performance" profiles experiencing both role clarity and role conflict. Therefore, in line with other scholars (van Veldhoven et al., 2020), we recommend that future researchers explore these possible interactions between job demands and resources.

Finally, as the well-being and performance profiles that we found in this study reflect patterns of realized outcomes of organizations across (some of the) financial and social goals, future research could also use the distribution of these profiles as organizational-level proxies for the intensity with which organizations engage in corporate sustainability. In addition, the distribution of well-being and performance profiles could serve as an indicator or outcome of the organization's perspective on the employment relationship. Using the profiles, scholars could, for example, identify the proportion of individuals in an organization who have sustainable work (those belonging to the "high well-being/high performance" profile) and investigate whether these organizations are more likely to adopt a mutual investment approach. A company with a mutual investment approach is one that typically invests heavily in its employees (e.g., providing training and development opportunities) and expects high employee contributions in return (Tsui, Pearce, Porter, & Tripoli, 1997).

Practical Implications

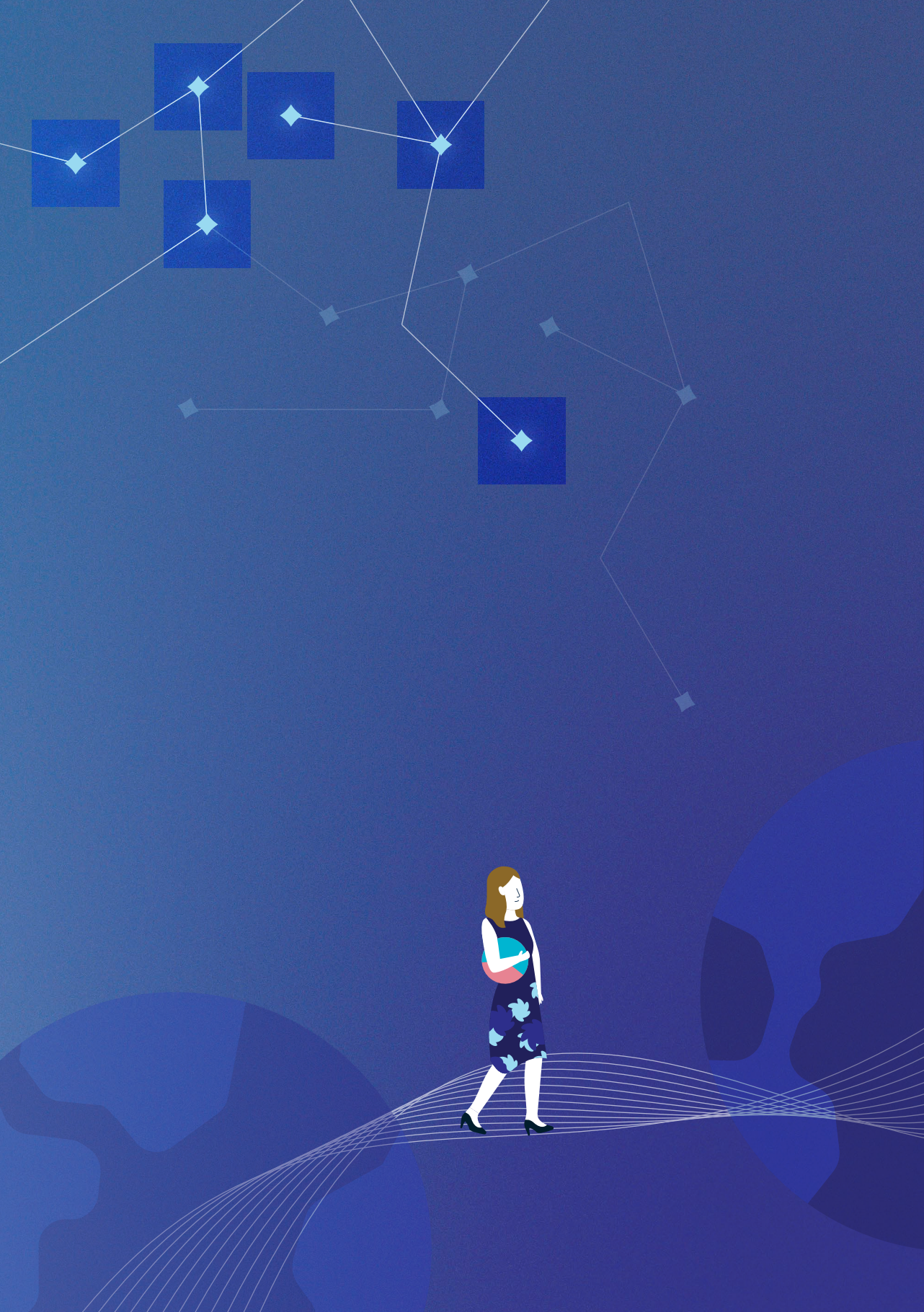
This research has several practical implications. First, a little over half of our sample provide support for the hypothesis that employees who feel well also perform well (e.g., T. A. Wright, Cropanzano, & Bonett, 2007). However, 41.2% of our sample was in one of the two profiles characterized by a trade-off between well-being and performance. This means that managers—preferably in close cooperation with their HR business manager—should consider these complex employee well-being/performance patterns when deciding upon an intervention. For example, to increase well-being and performance, managers should increase the job resources to which an employee has access if the individual is in the "low well-being/low performance" profile. These valuable job resources include learning and development, sufficient autonomy, and proper performance feedback. However, to increase the performance of the "high well-being/medium performance" profile, work pressure should be

increased. The latter is in line with the Crawford et al. (2010) assumption that challenging demands may motivate employees to perform.

Second, the largest single profile (30.4%) is the "high well-being/high performance" group, while relatively few are in the "low well-being/low performance" (12.1%) or "high well-being/top performance" (16.2%) profiles. This shows that situations in which employees have very limited resources and high hindering demands ("low well-being/low performance") are relatively rare and there is more to gain by further improving the performance levels of the "high well-being/high performance" group. Based upon our research, we suggest that managers could achieve this by enhancing the role clarity and feedback of employees in the "high well-being/high performance group." This could be done, for example, by being particularly attentive to role clarity when employees are new to their job during the socialization phase (Frögéli, Rudman, & Gustavsson, 2019). Alternatively, a manager may also work on his or her own style of feedback, making sure not to fall into the trap of micromanagement and instead focusing on the targets to be achieved and facilitating conditions (such as role clarity). This should ensure that employees are more receptive to feedback (e.g., Steelman & Wolfeld, 2018).

Conclusions

In pursuit of economic viability and social responsibility, many organizations strive to create jobs that increase employee well-being and organizational performance. Taking a person-centered approach, we identified five employee energy-related well-being and performance profiles, of which some have trade-offs (e.g., "low well-being/medium performance" and "high well-being/medium performance"). As each profile appears to be predicted by distinct job demands and resources, this study sheds light on the difficult task of creating jobs that are beneficial to both organizations and their employees.



6

Bridging the gap: How a shared PhD trajectory can benefit practice and academia to advance people analytics

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Introduction

Many organizations are interested in people analytics (Deloitte-Insights, 2018). People analytics refers to the usage and analysis of data related to human resources (HR) to make data-driven decisions and establish business impact (Marler & Boudreau, 2017). Using people analytics, organizations may, for instance, identify which internal employees to train to fulfill critical, difficult-to-hire vacancies (Peeters et al., 2020, chapter 1); predict turnover that is yet to come (Yuan et al., 2021); or investigate and improve the effectiveness of HR practices (Peeters, Paauwe & van de Voorde, 2021, Chapter 2). As such, it is believed that people analytics will help HR professionals become more strategic, enable them to demonstrate the financial impact of their HR initiatives, and in turn provide them with a long-cherished seat at the executive table (Angrave et al., 2016; Ferrar & Green, 2021; Guenole et al., 2017). Although many organizations have consequently begun to utilize people analytics, most people analytics experts are stuck at the basics, producing reports based on descriptive analyses and showing, for instance, headcount fluctuations. For them, using advanced analytics to uncover the antecedents of and predict the future for employee behavior, such as performance, seems to be a faraway dream, unattainable for many years to come (Cascio et al., 2019; Greasley & Thomas, 2020).

For academics, these types of insights are business as usual. In fact, for quantitative studies, anything less than root cause analysis would nowadays be unlikely to be considered for publication in an academic journal. As HR professionals generally lack the statistical knowhow, and since people who do have these skills often lack, on the one hand, the required knowledge or interest in HR theories to develop sound conceptual models and, on the other hand, the methodological skills required to test them (e.g. factor analyses, structural equation modeling), it has been suggested that through collaboration, HR academics may help organizations reap the benefits of people analytics (Angrave et al., 2016; Cascio et al., 2019; Simón & Ferreiro, 2018). Indeed, case studies in the past have illustrated that academics can help organizations gain valuable people analytics insights (e.g. understanding what factors contribute to store profit as well as why and in what stores turnover issues exist [Simón & Ferreiro, 2018]). At a more general level, it has also been suggested that the academic rigor, validation, external support, and credibility resulting from a collaboration between organizations and academics is beneficial for the latter (Zhang et al., 2015). In addition, for academics, collaboration has its own merits, such as access to data (e.g. large, longitudinal datasets from multiple actors), a higher likelihood that the findings of research are used in practice (i.e. impact), and that fact that papers resulting from a partnership between academics and practitioners are generally also cited more frequently by fellow scholars compared to non-collaborative work (Guerci et al., 2019; Shani et al., 2007; Simón & Ferreiro, 2018).

Despite these benefits, it is relatively rare for organizations and academics to collaborate. The almost antagonistic interests of academics and practitioners are suggested to be one of the primary reasons for this (Pasmore et al., 2007). On the one hand, academics are interested in answering generalizable and often time-consuming questions due to their focus on rigor and an interest in making a meaningful theoretical contribution. Therefore, an academic may, for example, be interested in understanding why employees leave any organization from a conceptual point of view, whereas organizations are looking for answers to their own questions, such as why people are leaving their specific organization, so they can take concrete actions to solve their problem. Thus, although the topic of interest may be the same, the desired research approach and outcomes can be vastly different for both parties. Moreover, two other factors diminish the likelihood of a partnership between academics and organizations. First, by involving practitioners in the research, the research itself and the study population are no longer separated, and the academic's role may become more of a consultant than a researcher. Observation biases may consequently occur, which could hamper the objectivity of the academic research (Guerci et al., 2019; Kilduff et al., 2011). Second, as academics lack contextual understanding, they may also not pose the right business questions, which means that the added value of the research remains limited for the organization (Rasmussen & Ulrich, 2015). These different interests, a fear of bias, and challenges resulting from the context have all contributed to the existence of the widely acknowledged gap between academics and practice (Beer, 2020; Zhang et al., 2015).

In recent years, academics have made efforts to shrink this gap by suggesting various types of collaborative research (Shani et al., 2007), designing frameworks on how collaborative research may be executed (Guerci et al., 2019), and establishing guiding principles to develop theory together with practitioners (Beer, 2020). To reap the benefits of a collaboration between academics and practitioners, one of the recommendations is to respect the unique strengths of the two parties and to introduce so-called bridging mechanisms, such as MBA and PhD enrollments (Guerci et al., 2019). In this paper, we describe our experience on a 4.5-year PhD trajectory in which the academic–practitioner gap is bridged by an individual who works both in academia and in the organization studied within the setting of people analytics. This solution presents a long-term partnership that allows academics and practitioners to remain within their own respective worlds while benefiting from a number of important aspects unique to collaborative research. For example, by working within an organization, the PhD student who is central to this paper was able to identify an important gap in the survey landscape of the organization, which led the research team to design a team-level survey. The resulting data allowed the PhD student and her academic supervisors to study the new phenomenon of agile working among teams, while limiting the risk of observation bias for these supervisors due to their distance from the study population (Chapter 4). Furthermore, we found that a joint

PhD trajectory provided valuable cross-fertilization within the new area of people analytics, as both parties shared their experience and knowledge network with each other. This led, among others, to an evaluation of a popular survey within the business and a qualitative paper on the working of people analytics departments for the research team (Chapter 3). However, due to the nature of a joint PhD, there are also challenges that are unique to this specific collaboration in an emerging field. These relate, for example, to earlier mentioned conflicting interests and the current state of the quality and accessibility of data within organizations. In summary, based on our real-life experience, in this paper we present the major benefits, the challenges, and their potential solutions for organizations, academics, and students who may be potentially interested in this type of partnership.

The partnership

For this PhD position, the Human Resource Studies (HRS) department of Tilburg University collaborated with a large multinational bank with headquarters in the Netherlands. Prior to this PhD position, both parties had been working together for multiple years and reaping the benefits of this partnership. For example, the organization provided guest lecturers and had access to the best students from the HRS department for internships, while the involved academics provided council to the organization's HR management team, jointly designed trainings and symposia, and conducted research on strategic topics at the request of the organization, for instance in the area of compliance and governance (Farndale et al., 2010). A relationship of deep trust consequently formed between both parties before they decided to further intensify this relationship through a shared PhD trajectory on the topic of people analytics.

For the organization, the decision was made to engage in a shared PhD trajectory on people analytics, as it was looking to accelerate the maturity of its people analytics department. Back in 2017, at the start of the shared PhD trajectory, the people analytics department had existed for three years and consisted of eight members: four fresh graduates and part-time students with a data scientist background, one data engineer, two reporting specialists, and one manager. At the time, the department had been primarily supporting a select number of HR initiatives, such as its traineeships, and it investigated whether, for instance, the average engagement score of employees differed between men and women. In short, the people analytics department was primarily focused on descriptive analytics and relatively far from the root cause analyses and predictive analytics it aspired to produce. Furthermore, due to the background of its members, there was first of all little knowledge of HR theories in general. Second, this also resulted in unfamiliarity with a large number of the research methods commonly found in HR research that are helpful to validate questionnaires and investigate the root causes of employee behavior; see Edwards and Edwards (2019) for more information on common research methods within HR

literature/research. Therefore, the organization wished to acquire the knowledge and skills by teaming up with Tilburg University.

From the university's side, the joint PhD trajectory was interesting for two of its senior researchers, who specialized in the field of strategic human resources management. They had already been working with this organization for a long time and were interested in conducting impactful research, accessing existing company datasets, and gaining further expertise in people analytics by working closely with an organization that was keen to establish an advanced HR analytics department. In the end, the two parties co-financed a PhD student who worked for both of them. This person conducted research of interest to both academia and the organization, transferred relevant knowledge about people analytics (projects) to the organization, and brought hands-on experience with this emerging new research field to the university.

Benefits of a joint PhD trajectory

1. Relevant research for academia and the organization alike

As with other forms of collaborative research, a joint PhD trajectory affords researchers the opportunity to learn directly from the organization what challenges it faces (Shani et al., 2007; Simón & Ferreiro, 2018). In our case, the research team found that the organization was implementing a new working method – agile ways of working – for all teams. Agile working originates from the information technology (IT) sector and encourages autonomy, self-reflection, a quick product turnaround, an efficient use of resources, close collaboration with stakeholders, and interactions through face-to-face communication (Beck et al., 2001). The resulting agile teams are typically relatively small, interdisciplinary in nature, and self-organized, and they do not have a hierarchical structure in place (Hoda et al., 2012). By working within the organization, the PhD student was also exposed to this new working method and gained hands-on experience with the practice. Interestingly, it appeared that the decision to implement agile working was primarily based on a belief instead of actual empirical evidence that it would work: Even within the IT setting, studies on the effects of agile way of working are scarce (Gren et al., 2020), and they are almost non-existent in the other functional domains (Hobbs & Petit, 2017). As such, this was an interesting topic for the shared collaboration for four distinct reasons. First, the organization was interested in assessing whether its decision to switch to this new working method had paid off. As a result, requests to study the effects of agile working were already coming in for the people analytics department. Second, although the department coordinated surveys targeting how people felt about their work and their organization, the surveys paid little attention to the (agile) teams. There was consequently a misalignment between the organization's strategy and the services offered by the people analytics department. This was resolved by asking the research team to design a team questionnaire that focused on agile teams. Third, the

research team was able to collect (quantitative) data through this newly developed survey. This was important from an academic point of view for two main reasons. On the one hand, despite the increasingly widespread implementation of agile working, empirical studies confirming that this approach is beneficial to teams are scarce. This is all the more so for functional domains outside of the IT setting (Hobbs & Petit, 2017). On the other hand, even less research has been devoted to the mechanisms that help to explain how agile working could positively influence team outcomes (Fagerholm et al., 2015). As the quantitative dataset we acquired through this research (Chapter 4) included different functional domains as well as an important mechanism from the team literature (psychological safety climate), it allowed the research team to contribute to the agile working literature. Fourth, and related to the previous reasons, the research team was able to conduct research on a topic that is currently of great interest to organizations and can thus expect to have societal impact with their work. In summary, a joint PhD trajectory can result in research projects that are relevant to the organization and the research team alike.

2. The time and opportunity to identify and address real and pressing business needs

Identifying research questions that are meaningful for the research team and the business is one of the earliest and most important steps for collaborative research (Guerci et al., 2019). At first, this partnership too struggled to find these types of research questions. Before the PhD student had officially started, the organization presented a number of topics to the research team that it believed to be worthwhile to investigate. All three topics related to large programs happening in the HR domain, such as the new global performance management program and the organization-wide leadership trainings. However, while the research team invested time into exploring the strategic HRM literature and writing up a research proposal, the business dynamics changed, and the initial enthusiasm about the "interesting research areas" faded away. Members of the organization were concerned about survey fatigue and openly debated the necessity of the project they had originally suggested. After all, the company did not currently have an issue with its leaders, so why investigate it?

This project consequently never got past the design phase. However, over the course of work on these projects, the PhD did identify other, more pressing issues. This is in line with other scholars, who suggest that it takes time to uncover the real issues that a research team can help resolve (Guerci et al., 2019; Werr & Greiner, 2007). For example, specifically in a discussion about the performance management program, employees argued that the entire team was responsible for the delivery of its products because all team members worked agile. As such, they believed it was not right to discuss individual performance to begin with. They did want to discuss their team performance and how to improve it, but until then, the HR function of the organization had paid relatively little attention to this. As a result, when the research

project on agile teams was created, a self-assessment team report that teams could use to discuss and improve their own team performance and behaviors became part of the deliverables. Specifically, while the research team designed the concept, the people analytics department further developed and automated the reports so that every team would receive this report when filling out the (academic) survey. Due to this addition, approximately twice as many teams as originally intended signed up voluntarily to fill out the survey study. Furthermore, although the research project has concluded in the form of a new publication (Chapter 4), the survey and self-assessment reports are currently being turned into a product of the people analytics department.

3. The creation of an extended knowledge network

Processes in which knowledge transfer, translation, and transformation take place are suggested to be an important element of successful collaborative research (Mirvis, 2007). However, as Simón and Ferreiro (2018) point out, it takes a long time before trust and knowledge of each parties motivations, interests, and working styles is developed when an organization and research team join hands. In our experience, the nature of the joint PhD established these informal processes in a natural manner, as PhD student worked multiple days a week for both parties. For example, although none of the student's projects initially focused on the people analytics' survey landscape, it became apparent by working within the department that there was room for improvement. As a result, the research team identified a number of issues through one of the leading surveys within the company; these issues served as input for important KPIs such as the overall engagement level of employees. The issues of this survey primarily concerned the way in which questions were formulated (e.g. clarity) and their construct validity (e.g. measuring their intended topic). The latter in particular appeared to be an issue, as questions intended to measure engagement also included questions that were more likely to be the cause of engagement, such as whether an employee had the required resources to execute their tasks. In the end, the research team conducted a number of analyses to assess the validity and reliability of the survey and found that the measurement quality of the survey was poor. This eventually led to the discontinuation of the survey and the end of the collaboration with the external supplier. The company was consequently able to save money, establish its KPIs on a higher-quality data source, and improve the quality of the survey data through its collaboration with the university.

The experience, reputation, and network of members within the organization also helped the research team. For one research project in particular, the research team aimed to identify factors that contributed to the effectiveness of people analytics departments from various other organizations using in-depth interviews with people analytics experts and their stakeholders (Chapter 3). The rationale for this research was that the organization in question, its peer organizations, and the scientific

literature on people analytics could benefit from this knowledge for three main reasons. First, the field is in need of an empirically grounded framework on people analytics (Fernandez & Gallardo-Gallardo, 2020; Qamar & Samad, 2021). Second, to this end, clarity is needed on a) the relationship between the different elements a people analytics function requires, b) the inputs, processes and outputs a people analytics function requires to be effective, and c) the viewpoint of the recipients of these outputs, the stakeholders of a people analytics function. (Margherita, 2021; Peeters et al., 2020). Third, these insights may equip organizations that are struggling to establish their people analytics department with the knowledge of how to conduct people analytics effectively.

However, to investigate these matters, the research team needed access to people analytics experts and their stakeholders from various companies. Through the network of the people analytics leader and the reputation of the company, the research team found that many organizations responded favorably to their request to participate in this research. The research team was thus first able to collect a qualitative dataset consisting of the opinions and personal experiences of stakeholders and members of advanced people analytics departments from various companies, which is a rarity in the field. Second, this also allowed the team to contribute to the development of theory on people analytics, which is still relatively practitioner focused. Third, as the organization still had much to learn about people analytics itself, this research also provided it with a richer understanding of how to facilitate the effectiveness of its own people analytics department.

Finally, practitioners' and academics' broader networks may also be used in each other's favor. For example, when an HR professional from outside of the people analytics team sought academic support on diversity and inclusion, the research team connected them with fellow scholars who are fully dedicated to the topic. Therefore, this knowledge network can also be beneficial outside of the narrow scope of the collaborative research setting on people analytics.

4. Follow-up in practice

Research has shown that practitioners hardly invest any time in reading academic papers (Rynes et al., 2007). This disconnect between science and practitioners has long been a concern of academics (Beer et al., 2015; Guerci et al., 2019) and is becoming ever more pressing nowadays. As a result, academics within the Netherlands who were once exclusively recognized for research output will, in line with the new "recognition and appreciation" program of Dutch universities, also be appreciated for impactful and relevant research for organizations, teaching, leadership, and team spirit (Ruimte voor ieders talent, 2019). In the case of a joint PhD research, there is practical relevancy and impact by default, as at least one organization is interested in the findings of the study. The following specific example, in which the research

team worked together with another HR stakeholder outside of the people analytics team, demonstrates this quite clearly (Chapter 5). The stakeholder was one of the few parties outside of the people analytics department in charge of a specific survey. This survey contained information related to the well-being of employees. However, thus far and with the aid of a consultancy firm, the stakeholder had primarily been showing how, on average, the organization scores on several well-being indicators (e.g. work pleasure, energy, and burn-out) and how these scores deviated from the benchmark. Therefore, there was only a generic level of understanding of the root causes that may be based on the scientific literature, but no business-specific insights. To this end, the research team worked together with the (by then more advanced) people analytics experts of the organization and investigated what factors contribute to employee well-being within the organization, among other things. Furthermore, the research team provided insights into specific employee well-being and performance combinations (so-called profiles) and demonstrated that counter-intuitive combinations, such as employees with high well-being scores but relatively poor (self-rated) performance scores and employees with low well-being scores and relatively high (self-rated) performance scores, existed within the organization. In addition, possible antecedents were also identified, such as autonomy, learning opportunities, and work pressure. Before the article was published, the stakeholders were already informed of the findings and received suggestions on how to work with them. The stakeholders themselves brought the findings to top management to ensure that investments would be made based on the findings. The fact that this research was published also boosted the credibility of the findings. For the research team, this project resulted in a publication with a large dataset (5,700 employees) on a topic that is relatively underexplored (combinations of well-being and performance) and with nine possible drivers to explain why a specific combination of well-being and performance may occur (Peeters, van de Voorde, & Paauwe, 2021, chapter 5).

Finally, the people analytics department also benefited from this collaboration. Through the initial collaboration between the research team and the HR stakeholder, the people analytics department also became involved. They now have stakeholders eager for advanced analytical insights (e.g. root cause analyses, predictive analytics), which is a rare occurrence for people analytics stakeholders. Furthermore, as the survey is repeated every year, there is a steady influx of new queries from these stakeholders for these types of insights.

5. The usage of existing data

Although organizations nowadays have a large volume of data, academics are generally not provided access to these datasets (Zhang et al., 2015). The research team experienced four main benefits of a joint PhD student with regard to data access. First, the team was able to access data within the organization. This was a rarity, as even interns working within the organization were denied access to analyze

employee data for their thesis projects. Second, the PhD student was able to identify and work with interesting existing datasets from the inside, such as the one described in the previous section. This is also beneficial from an ethical perspective, as it means that a research team could utilize data that has already been gathered. Third, by collaborating with the company, (new) datasets could also be enriched by combining them with other datasets, such as data collected in previous years (longitudinal data) or objective data (e.g. performance ratings, sales data). Fourth, by having an in-depth understanding of the organization and access to people who have more insights when required, the research team can place the data within its context. The organization involved in this collaboration had, for example, a matrix structure, which meant that the hierarchical structure within the company was not always straightforward to interpret. Since a lack of understanding of this structure could result in incorrect conclusions, the joint PhD trajectory helped to avoid this type of misunderstanding.

For the organization, there were three main benefits of sharing its data with the research team. First, in many cases, the data gathered by the organization remained underutilized. For example, the dataset that we described in the previous section had been gathered several years before the research team used it. This means that the organization always had the possibility of investigating the drivers of employee well-being and performance, but did not do so until a year ago due to a combination of a shortage of knowledge of the HR literature, a lack of know-how regarding behavioral science research and analytical skills, and other priorities. By analyzing this dataset, the research team demonstrated the potential of this dataset and shared relevant findings with the organization. Second, the people analytics department had far more project requests than it had the time and resources or manpower for. By teaming up with the research team, the department could share some of this burden with the involved academics while still obtaining high-quality answers to the questions raised by stakeholders. Third, the research team also provided guidance with regard to the data that was collected by the organization. As mentioned previously, through the analysis of existing data, the research team found that one survey, provided by an external commercial survey agency, was of relatively low quality, which affected any insights that could be derived from it. By tackling this issue, the organization was able to improve the data quality available to the people analytics department.

6. Preferred partners

Although this PhD trajectory was born from a long period of collaboration between the involved organization and academics, the PhD trajectory further intensified the relationship between the two parties. This is because a PhD trajectory takes multiple years, and the involved academics and organization hence also collaborate for the same duration. During this time, the two parties frequently interact and support each other in other areas (e.g. guest lecturers), which further reinforces the pre-existing bonds of trust. The research team and organization consequently decided to prolong

the collaboration and appointed a new PhD student once the initial PhD trajectory had been completed. In our case, the university became the preferred supplier of PhD students for the people analytics department. Therefore, the research team may benefit from the experience and knowledge from the previous PhD student and conduct follow-up research on topics already studied. For the organization, this also saves time, as it will be easier to pinpoint new and interesting research topics for both parties.

Challenges of a shared PhD position

1. Different potential gains

As described in the introduction, the collaboration between academia and organizations is sometimes difficult due to conflicting interests (Pasmore et al., 2007). During the shared PhD trajectory, we too faced tensions. Both parties decided that a questionnaire would be most suitable to conduct the agile research. For the research team, there were several benefits of using validated scales of previously published research. First, this would ensure that the survey would be of high measurement quality; second, it would increase the chances of the resulting manuscript being published in a high-ranking journal; and third, no time needed to be invested in designing a survey and performing the thorough reliability and validity analyses that are required for newly developed surveys. For the organization, however, the use of scales designed by other researchers was less advantageous. This is because, first, questionnaires designed by academics are often relatively large, as multiple items are required to measure the same construct; second, they lack the necessary business context to ensure their generalizability and – most important – their use for commercial purposes. The latter disadvantage implied that the survey could only be used by the organization as long as it collaborated with the academic research team on a research project, which conflicted with the interest of the organization of offering the use of the survey to the teams for an undetermined time without any involvement of the university.

Possible ways to navigate these tensions: Although we believe that conflicting interests cannot be avoided in a joint PhD trajectory and collaborative research in general, a PhD operating in both worlds will be able to quickly identify and interpret the conflicts, overlaps, and leeway for both parties. For example, in the case described above, it was critical for the organization to be able to use the survey after the collaboration ended with the research team. Luckily, as the research project delved into a relatively new topic, there was no golden standard with regard to how to measure agile working. This meant that there was leeway for the research team to build on available literature on related team constructs as a guideline. However, to ensure that the survey was of high quality and that the research team could test it through statistical analyses, the questionnaire – with 82 questions – became larger

than the organization initially intended. However, the organization could compromise on this, as it would benefit from a high-quality survey. Therefore, the organization agreed to send out this long survey on the condition that the research team would advise on how to best condense it for future use. In the end, a reliable, 20-question survey remained that the organization could use in the future to provide teams with feedback on a wide array of behaviors and performance. As such, we managed to navigate through the tensions from both sides and reached a middle ground that was acceptable for both parties.

2. The quality, accessibility, enrichment, and ability of data collection

As mentioned before, working with the data of an organization comes with a number of benefits for the research team and the organization alike. However, we found that there were also many challenges with regard to the data quality, accessibility, and enrichment, as well as the possibilities of gathering new data during this joint PhD trajectory. First, as has been noted by Andersen (2017), for example, many people analytics departments still struggle with the quality of their employee data. Challenges relate to the myriad definitions within the same organization about what it means to be a "full-time employee," human input errors when recording the data, and inconsistencies in functional titles, among other things. This meant that many research projects could simply not be done due to the risk of producing incorrect conclusions and the large effort it would take to clean up the data. On top of that, we also noted that there were different opinions about the quality of the existing survey data. For instance, the senior management of the organization preferred a certain survey primarily due the extensive benchmark and reporting features, whereas the research team viewed it as subpar from an academic point of view due to issues with the question formulation (e.g. vagueness by referring to "managers" in general, double questions, and "leading" questions [asking the respondent whether *the organization innovates and whether these innovations are seen as positive* in a single question]) and construct validity. Therefore, they concluded that it could not be used for academic research. As such, many potential research projects were impossible or had little benefit for one of the parties.

Second, with respect to accessibility, there were challenges concerning the confidential and sensitive nature of employee data. For example, whereas it was business as usual for the research team to ask about "work pressure" and "burn-out symptoms," the organization's data privacy officer considered these questions to be health data according to the General Data Protection Regulation (GDPR) and thus subjected it to the stringent confidentiality treatments after discussion with legal councilors. As such, the research team was not allowed to combine this data with any demographical data, even though it is common practice among academics to control for topics such as gender or age and describe the study sample.

Third, during the duration of the PhD trajectory, the research team was not able to enrich datasets with another existing dataset (e.g. HR system data, performance data, absenteeism) for two main reasons. a) As mentioned above, the team was not allowed to enrich certain datasets due to the sensitive nature of the topic (e.g. burn-out symptoms). Specifically, as the researchers aimed to analyze the data at the individual level, the data privacy officer was (understandably) concerned that the research team could trace individual responses back to a specific individual when too much demographical data was provided (e.g. team identifier, gender, age). b) Although the research team was granted permission to enrich data if explicit consent was given by the respondents, existing datasets simply could not be enriched due to the way in which they were created. This was because, up until a year ago, all surveys sent out by the organization were fully anonymous. This meant it was impossible to enrich the data or to create longitudinal datasets, as no identifier variable (e.g. e-mail address, personnel number) was present within the dataset.

Fourth, regarding the gathering of new data, we experienced that the research team was interested in sending out academic surveys for the previously reasons described, whereas the organization was concerned with survey fatigue and would rather have analyses performed on the (underutilized) datasets that were already available. Therefore, the collection of new qualitative survey data for a new research project was difficult to execute.

Possible ways to optimize the use of (existing) data: In our experience, the people analytics department within the organization has made great strides to improve the quality, accessibility, and enrichment options of its datasets. After all, it is of high importance to the department that the data is of high quality. Furthermore, like the research team, the people analytics department also faced issues with regard to the accessibility and enrichment of data. During the PhD trajectory significant steps were therefore taken with regard to the procedures and the ease of acquiring and combining datasets. With regard to the procedures, the norm was to gather anonymous survey data to ensure the privacy of the respondents could be protected at all times. In the past year, the people analytics department has challenged this norm. As it gained the approval and trust of the involved data privacy officers to collect datasets that can be linked at the individual level with other data under specific conditions, it is now allowed to create longitudinal and mixed datasets. Additionally, the ease of acquiring a new dataset shows in the following example. Several years ago, it took the people analytics team three months to gain access to the 2017 version of the dataset that was used for Chapter 5 (2020 version). This was back when the GDPR, accompanying procedures, and relationship with the data privacy officers were still new. In contrast, the 2021 version of this dataset was acquired in only a few days. Therefore, it is our belief that as the maturity of the people analytics department progresses, the challenges faced during the joint PhD

trajectory with regard to the data will also diminish. In general, we believe that it is important to make use of the relationships and company knowledge that are built over time on a shared PhD trajectory. Whereas the research team was originally unaware of promising datasets, the PhD student discovered them while working for the company. Furthermore, as we will later explain, we believe that it can be highly beneficial for the company and research team to collect data for a joint research project, as was done for the research on agile teams. However, since this is a time-consuming and risky venture, it is also important to make optimal use of a number of the existing datasets that are already present.

3. The different ways of working

Common to a PhD trajectory within the Netherlands is that a PhD student develops research proposals in their first year and spends the subsequent three years executing these projects and writing the dissertation. This is logical within the academic setting, as it generally takes several months to write a manuscript and at least several more before it is published. However, for a company, strategic priorities are ever changing, and once a company is committed to a research project, it should be executed sooner rather than later. For this reason, three of the initial projects that the organization and research team agreed on were ultimately canceled at the request of the organization. Moreover, when working on the projects, there were many instances in which the literature search and the research design had to be done within a faster time scope than is common within academia. Therefore, the research team sometimes had to deliver on time schedules more commonly found among consultants than academia, but was able to use the enthusiasm and need of the business to push forward with the research agenda faster.

Furthermore, research conducted by the people analytics department itself suffered from the volatile context of the company. For example, an experimental study focused on the new hybrid working situation aimed to track and compare the working experience of employees who had returned to the office for various days a week in comparison to workers who continued to stay at home. However, as restrictions lifted quicker than expected, businesses decided to drop their control groups or return to the office faster than the people analytics department could keep up with (e.g. translations, legal approvals required for the survey). Although this was unfortunate for the people analytics department, such a turn of events would have been disastrous for an academic study. Therefore, the time the academic team requires to plan and design sound research, provide insights, and eventually publish an article is vastly different from the reality, speed, and need for action of the organization.

<u>Possible ways to align the different working methods:</u> In our experience, it worked best for the research team to have a strong understanding of the current state of

(strategic) human resource management literature and for the PhD student not to plan more than two years ahead. In this way, the research team could conduct research on topics relevant for both parties without compromising on the quality of the research. Moreover, in our collaboration, we found it that it worked well that the research team would provide the insights to the organization just a few weeks after the data collection had been completed, while taking the time to write the manuscript and submit the paper in the months to follow. Finally, although it is tempting to collaborate on volatile, high profile projects like the hybrid working research, we also found that there were too many differences in how the research team and organization worked to be able to truly benefit from each other here. Instead, we found it was better to follow the more stable and/or predictable strategic priorities of the organization, like setting up a people analytics department (Chapters 2 and 3) or focusing on employee well-being and performance combinations (Chapter 5).

4. The political arena

In a joint PhD trajectory, the political arena of the organization can be a specific challenge to work with for both parties. This was especially evident in one specific research project. In this case, the research team offered to investigate the effects of an earlier project executed by the people analytics department, in which they had supported a large redeployment effort of the organization. Specifically, based on the skills, preferences, and open positions within the company, the people analytics department created an algorithm that recommended managers to consider – on paper – suitable candidates for a position in their team. The decision was left to the manager, and data was available that provided insight into when and why a manager had made decisions similar to or contrasting with the algorithm. The research team and the people analytics department were interested in determining whether the recommendations by the algorithm had been correct in hindsight, in terms of the well-being and fit employees experienced with their new job. This was an interesting question for two primary reasons. First, it answered Van der Laken's (2018) call for research; the author stated that there are still relatively few case studies that explore the empirical value of people analytics. As the algorithm used in the redeployment process is a direct result of the application of people analytics, this study would answer his call. Second, although algorithm-based and -supported decisions have been in existence for decades in the recruitment domain (Grove, Zald, Lebow, Snitz, & Nelson, 2000; Kuncel, Klieger, Connelly, & Ones, 2013), they are rarely used in the redeployment area. Therefore, within the redeployment context, the aim was to compare whether the redeployment decisions in which the manager and algorithm agreed, led to higher well-being, person–job fit, and performance, compared to decisions in which the manager deviated from the algorithm.

Despite enthusiasm from the people analytics department, the workers' council, and a few senior managers, others (primarily senior managers) were deeply concerned

about the research: They feared it would open up old wounds and stir up unrest in the organization. Furthermore, as an academic party would carry out the research, they also feared that they would not be able to control the narrative of the research. Therefore, despite the research having overcome many challenges and passing numerous approvals (e.g. workers' council, unions, and many senior managers), the research was canceled just a week before the launch. This meant that the research team and members within the organization had spent months on a research project that would not be carried out.

Possible ways to manage the political arena: Based on the previous experience, the organization and research team decided to invest time in projects that were less sensitive in nature and on which they had more control. This implied that the project either had to make use of existing data (e.g. Chapter 5) or had to be owned by the people analytics department (e.g. Chapter 4) and not by a different HR sub-domain, as was the case for the earlier described performance and leadership initiative. Furthermore, for all research projects that followed, the availability of sufficient senior management support was ensured from the outset. This was done by discussing the initiative with the HR management team both in the early stages and throughout its execution. In this way, another situation similar to the redeployment evaluation initiative could be prevented.

5. It takes time to obtain the required familiarity and credibility

Within a joint PhD trajectory, a PhD student and their familiarity and credibility with(in) an organization and a university are crucial to identify and execute academic research (opportunities). However, we found that developing this familiarity and credibility takes more effort than simply working on the academic research relevant for the company. The PhD student central in this paper initially also aimed to develop familiarity and credibility by focusing primarily on the research projects that the organization and university had agreed on. This was a logical objective, considering the limited time frame of a PhD and the job description. However, this resulted in a situation in which the student was predominantly working on academic research, while the other experts within the people analytics department worked on other projects. Therefore, the PhD student had few opportunities to build the professional familiarity and credibility required among the people analytics experts, even though interpersonal relationships were formed due to her office presence for multiple days a week.

Possible ways in which to attain familiarity and credibility with an organization: In our experience, it was of critical importance for the PhD student to step out of her own bubble and work on projects with members of the people analytics team who were not immediately related to the research projects. In doing so, she could demonstrate the added value of her knowledge and skills and become a valued colleague. This

opened new doors for her and provided inspiration for potential interesting areas of research that were beneficial to the organization and the research team. Therefore, we believe that during the first months of a joint PhD, the student should primarily work with members of the organization, build credibility, and learn about the organization. A literature review, such as Chapter 2, or research on an existing dataset, such as Chapter 5, are potential prime ways to spend research time well if a PhD student is still learning the ropes and becoming acquainted with the unwritten rules within an organization. Through this investment of time, we believe that a large number of benefits will be more easily attainable, and challenges more easily solved.

Conclusion

While many organizations are interested in people analytics to enhance strategic decision making, illustrate and improve the added value of HR activities, and gain influence in the C-suite (Angrave et al., 2016; Ferrar & Green, 2021; Guenole et al., 2017), many people analytics departments get stuck in producing basic metrics reports (Cascio et al., 2019). In line with the suggestion of various scholars (Angrave et al., 2016; Cascio et al., 2019; Simón & Ferreiro, 2018), we found that collaboration between academics and an organization in the form of a shared PhD may indeed help the people analytics department acquire the required theoretical and statistical knowledge to become a more mature function and transition from producing simple reporting metrics to offering advanced analytical insights. Specifically, the people analytics department central to our partnership transformed in the 4.5 years of our collaboration. The department currently consists of 15 members with mixed backgrounds. While a large number of members still have a data scientist background, a number of HR professionals and researchers have also joint its ranks. Furthermore, although the department maintains a dashboard with metrics on the most important KPIs, it also investigates what is on employees' minds through sentiment and topic analysis; has a thorough understanding of the root causes of important employee outcomes (e.g. well-being); provides insights into the knowledge, skills, abilities, and other characteristics the organization needs to develop to be prepared for the challenges of the future; and much more. As many of these projects are of strategic importance, insights are frequently shared with top management, and the hierarchical position of the department reflects the importance that is being placed on the findings: The people analytics leader directly reports to the chief HR officer and the chief analytics officer of the bank. Although this significant transformation can by no means be attributed solely to the organization's partnership with academia, we do believe that it serves as a small piece of the puzzle that was required for the people analytics department to live up to its promises, deliver strategically relevant insights for the bank, and enable the chief HR officer in the board room (Angrave et al., 2016; Guenole et al., 2017).

As with the organization, the involved academics also benefited from this partnership. In the 4.5-year partnership, the research team managed to collect new data and make use of existing datasets on emerging topics (e.g. factors impacting the effectiveness of a people analytics department [Chapter 3], the new phenomenon of agile teams [Chapter 4]); conduct relevant research for organizations and academia (e.g. insights into well-being and performance profiles [Chapter 5]); and write four research manuscripts, two of which have been published and another two of which are in the revision process of peer-reviewed journals. Moreover, the PhD student in question was able to complete her dissertation.

In conclusion, both the academics and the practitioners experienced many benefits from their collaboration through this shared PhD trajectory. Based on our experience, we believe that the factors that contributed to the earlier mentioned large gap between academics and practitioners, such as the required familiarity with the context to ask the right business questions (Rasmussen & Ulrich, 2015), observation biases (Guerci et al., 2019), and the conflicting values of both parties (e.g. Pasmore et al., 2007), can be bridged by a joint PhD trajectory for three main reasons. First, through this construction, a PhD student is able to gain an in-depth understanding of an organization over time. Second, as the student's academic supervisors themselves remain at a distance, the biases to which the PhD student is subjected can be canceled out by the academic supervisors. Third, as a shared PhD trajectory is often the result of many years of collaboration in the form of, for example, guest lecturers, internships, advising, and joint research projects, the deep trust between both parties that develops over time is further enhanced through the joint PhD trajectory. This trust enables an organization and a research team to navigate the challenges with satisfying outcomes for both parties. In summary, we believe that by bringing a person who is both a researcher and a practitioner into the equation, the academic–practitioner gap can be bridged, and both organizations and academics can reap the benefits of this partnership, especially within the context of people analytics.

7

Discussion

Introduction

Fueled by the success stories of large (tech) companies and an ever-increasing amount of data (Ellmer & Reichel, 2021; Ferrar & Green, 2021; Minbaeva, 2021), organizations are eager to use people analytics to their advantage (Ledet et al., 2020). People analytics refers to "the analysis of employee and workforce data to reveal insights and provide recommendations to improve business outcomes" (Ferrar & Green, 2021). Within this dissertation, I followed the SHRM multiple stakeholder perspective and defined business outcomes in terms of employee well-being and performance (Beer et al., 2015; P. F. Boxall et al., 2007; Paauwe & Farndale, 2017). Despite the enthusiasm of business leaders about people analytics though, most organizations struggle to adopt it effectively: Whereas the success stories about people analytics are often based upon insights and recommendations from more advanced people analytics, such as root cause analyses (i.e. regression), predictive analytics (e.g. which individuals are likely to leave the company? (Yuan et al., 2021)) or machine learning (e.g. to find out the topics employees talk about in replies to open-text questions), most organizations get stuck at the basics (Cascio et al., 2019; Ledet et al., 2020). This means that they only provide insights that relate to, for instance, headcount and engagement fluctuations (Orgvue, 2019; Sierra-Cedar Inc., 2019). As a result, many people analytics departments fail to drive (strategically) relevant insights and recommendations that can improve employee well-being and performance (Jörden, Sage, & Trusson, 2021). Therefore, the primary question of this dissertation aimed to answer was:

> *How can people analytics be used to gain insights into and provide recommendations to enhance business outcomes?*

To answer this question, this dissertation addressed three key challenges within the people analytics literature: 1. How can a people analytics function be created that enhances employee well-being and performance? 2. How can people analytics be used to enhance well-being and performance? 3. How can people analytics departments benefit from a collaboration with academia? In this chapter, I will discuss the main results related to each of these key challenges and this dissertation's theoretical contributions. Furthermore, I will reflect beyond these three challenges on using people analytics, discuss the strengths and limitations of this dissertation, and its practical implications. Finally, I will conclude with an overall conclusion.

Overview of the main results for each of the three key challenges and theoretical contributions

Challenge 1: How can an effective people analytics function be created?

Summary of the main findings
A narrative literature review was presented in chapter 2 of this dissertation to address how an effective people analytics function can be created. This literature review builds upon a rapidly increasing amount of people analytics literature (Qamar & Samad, 2021) and literature on the broader, more advanced, business intelligence domain that people analytics is part of (Davenport & Harris, 2017; Holsapple et al., 2014). The findings revealed that an effective people analytics team required four things. First, it requires several enabling resources (e.g. data). Second, it needs to turn these resources into products (e.g. research) that provide insights and recommendations in support of people-related decisions. Third, the stakeholders the team should serve (e.g. leaders), collaborate with (e.g. other analytical teams) and those whom it affects (e.g. employees) were identified. Fourth, it needs a governance structure that helps the team deliver the insights and recommendations in a compliant and legitimate manner. These findings were synthesized in a heuristic model, the "People Analytics Effectiveness Wheel", which provides a clear graphical illustration of the elements a people analytics team requires to be effective.

On top of these findings, the literature review revealed that it is still unclear how the enabling resources of a people analytics team are transformed into products. Furthermore, questions remain about how the elements identified as crucial for a people analytics function relate to each other. Therefore, I explored in chapter 3 what inputs, processes, and outputs a people analytics function requires to be effective through 36 in-depth interviews with members of nine people analytics departments and their stakeholders. Overall, this led to three important findings. First, I was able to identify additional elements that a people analytics function requires on top of the findings presented in chapter 2. These were, for example, the culture within the organization, consultancy services (e.g. people analytics departments helped stakeholders identify the "question behind their question" and track their strategic priorities), and activities to build the analytical capabilities of stakeholders. Second, eight processes were identified to transform the inputs into outputs. Some of these related to the projects of a people analytics function (i.e. project selection, management, execution and the compliant and ethical behavior of people analytics experts) and others to its stakeholders (i.e. the attitude of stakeholders, collaborations, partnerships and the transparency of people analytics function to their stakeholders). Finally, an empirically grounded framework on how an effective people analytics function was created. Specifically, the "People Analytics Effectiveness Framework" was established with seven propositions to guide future research on

the topic. These propositions illustrated on the one hand the relative importance of the different elements identified in the framework. For example, having data was found to be more crucial than a specific organizational culture. On the other hand, the propositions showed the relationships between the different elements: Delivering high-quality people analytics products, for instance, increased the reputation of the people analytics function. Furthermore, as the reputation increased, people analytics functions were typically provided with more inputs and better contextual factors, such as access to new datasets and increased support from senior management.

Theoretical contributions

I have addressed how an effective people analytics function can be created within this dissertation through a narrative literature review and qualitative research. This is important, as there is a rather limited theoretical understanding of how people analytics can be implemented effectively within the people analytics literature (Fernandez & Gallardo-Gallardo, 2021; Qamar & Samad, 2021). Specifically, the current models available within the people analytics literature provide limited guidance because they are based upon literature reviews, case studies from a single company, or are too practitioner-oriented. Therefore, this dissertation contributed to the people analytics literature in three ways.

First, in contrast with other models based upon literature reviews (i.e. Opatha, 2020; Shet et al., 2021), the literature review presented in this dissertation did not only include studies from the people analytics literature. Instead, it also included studies from the broader business intelligence literature. As a result, chapter 2 identified additional elements crucial for a people analytics function which remained undetected within other literature reviews. These are, for example, the governance structure of the function (e.g. hierarchical position within the organization) and the ethical use of the data. As these elements have been identified as important within other studies (e.g. Green, 2017; Tursunbayeva et al., 2021) and chapter 3, this dissertation provides a more complete understanding of what it takes to execute people analytics effectively.

Second, chapter 3 builds upon data of nine different companies instead of the single case studies presented in the people analytics literature thus far (i.e. Anger et al., 2021; L. Liu et al., 2020). As a result, I was able to compare how different people analytics departments operated and developed a more in-depth understanding of the people analytics function compared to single case studies. This also showed in the results. Specifically, this dissertation concluded, for instance, that people analytics should serve various decision-makers (e.g. managers, HR, employees) in line with other scholars within the field (Ellmer & Reichel, 2021; Ferrar & Green, 2021; Guenole et al., 2017). In contrast, the models build upon single case studies seem to pursue only the interest of HR (i.e. Anger et al., 2021; L. Liu et al., 2020). As a result, the

findings from this dissertation are more generalizable and complete compared to prior work.

Third, the framework presented in chapter 3 adds to our understanding of how inputs are transformed into outputs, the relative importance of the different elements and their relationships. This was missing from the relatively simplistic practitioner-oriented models (i.e. Ferrar & Green, 2021; Guenole et al., 2017) and also in our People Analytics Effectiveness Wheel. For example, whereas the model of Ferrar and Green (2021) identified data and the organizational culture as critical elements to a people analytics department, chapter 3 showed that while both are important, data is a must-have and a favorable organizational culture a nice to have. This is because a people analytics function cannot provide insights nor recommendations without data, while the organizational culture can help or hinder the function. For instance, whereas a function will struggle to access certain (sensitive) data (e.g. salary or absenteeism data) within a company that is risk-averse, they can use other data as a work around or influence the data protection officer through senior management to receive access to the data. Furthermore, it was found that if a people analytics function provides high-quality outcomes, indirect outcomes, such as the reputation of a people analytics function, increase. As a result of the increased reputation, the function can, in the future, for example, benefit from more senior management support or more accessible data. All in all, this dissertation therefore offers the people analytics literature a richer and empirically grounded framework.

Challenge 2: How can people analytics be used to enhance employee well-being and performance?

Summary of the main findings

To illustrate how people analytics can be used to provide insights and recommendations that can enhance employee well-being and performance, I presented two people analytics use cases. First, in chapter 4, I demonstrated how people analytics can be used to evaluate a company's strategic decision. Specifically, organizations are rapidly implementing the agile way of working because they expect it to lead to higher employee well-being and performance (Edmondson & Gulati, 2021). However, while the agile way of working may appear successful within the Information Technology environment it originated from, scholars are concerned it may "fail" (Kruchten, 2013) or prove "unsuitable" (Edmondson & Gulati, 2021) for other contexts. Therefore, I assessed whether the decision of a large financial company to implement the agile way of working across the organization leads to beneficial team outcomes like top managers expect. To do this, I developed a survey focused upon the agile way of working and tested among 97 teams from this organization whether data can support these positive expectations. Based on my research, I found that the agile way of working is related to team engagement and performance regardless of

teams' functional domains. Moreover, I find that these effects are partially mediated by psychological safety climate. Psychological safety climate refers to a shared belief among team members that they can take interpersonal risks and can be, for example, open about their mistakes (Edmondson, 1999). Based upon this research, the company has data-driven insights that support the decision to implement the agile way of working across various functional domains.

Second, in chapter 5, I demonstrate how people analytics can be used to provide insights about employee well-being and performance and inform job design practices. Specifically, I tested whether complex trade-off patterns may occur between employee well-being and performance in line with SHRM literature (e.g. Ayala et al., 2017; Peiró et al., 2019). It is especially relevant to examine combinations of well-being and performance in organizations, because most HR practitioners believe that employees who feel well, will also perform well and design their HR policies accordingly (Peiró et al., 2019; Peiró et al., 2021). Based upon data of 5,729 employees working in a large financial organization, I find support for the notion that five well-being and performance profiles exist: 1. Low well-being/low performance, 2. low well-being/medium performance, 3. high well-being/medium performance, 4. high well-being/high performance, and 5. high well-being/top performance. Furthermore, I found that specific job demands and resources are related to these well-being and performance profiles. Specifically, employees with more learning and development opportunities, more social support from colleagues, more autonomy, and less role conflict were related to the high well-being profiles. Additionally, employees with more role clarity, more performance feedback, more autonomy, and less work pressure were related to the high- and top-performance profiles. Finally, communication and social support from the manager were found to be relatively weak antecedents of the different profiles. As roughly 40% of the employees showed a trade-off pattern (i.e. Low well-being/medium performance or high well-being/medium performance), this study illustrates that HR professionals from this company should consider these different performance and well-being combinations in their HR policies and specifically when they (re)design jobs. Moreover, it provides them with guidance on how to increase the number of employees with a desirable combination (i.e. high well-being/high performance or high well-being/top performance), so that employee well-being and performance increase across the organization.

Theoretical contributions

Within this dissertation, I provided two use cases on people analytics. On the one hand, I demonstrated how people analytics can evaluate whether the decision of senior management to implement the agile way of working resulted in the expected team engagement and performance gains for a company in the financial sector. On the other hand, I illustrated how people analytics can provide insights about employee well-being and performance and inform the company's job design practices. Through

these two use cases, I answered the call to conduct more empirical research on people analytics (Marler & Boudreau, 2017; Qamar & Samad, 2021), and in particular, to illustrate how people analytics can be used to support the interest of employees and managers (Margherita, 2021). This is my first contribution to the literature.

Additionally, these two use cases also contributed to their own respective research field. Specifically, the use case on the agile way of working contributed to the team literature in three ways. First, it provided empirical, quantitative support for the positive expectations around the agile way of working. Specifically, it showed that the agile way of working is beneficial to team engagement and performance. This is important, because there is a scarcity of empirical quantitative studies on the topic despite its rapid implementation rate in practice (Edmondson & Gulati, 2021). Second, it found empirical support that psychological safety climate is an important mechanism that explains why the agile way of working is beneficial. This confirms the widespread reasoning that the agile way of working indirectly leads to increased team outcomes (Buvik & Tkalich, 2022; Melo et al., 2013; Tripp et al., 2016; Wood et al., 2013). Third, despite the warnings of, for example Kruchten (2013), the study showed that the benefits can be expected across various functional domains.

The second use case, contributed to the SHRM literature. Thus far, scholars have primarily used a variable-centered research design to study well-being and performance (Benitez et al., 2019). This is problematic, as research has indicated that complex trade-off patterns may occur between well-being and performance, which cannot be found through a variable-centered approach (Peccei & van de Voorde, 2019; van de Voorde et al., 2012). Therefore, this study contributed to the emerging field in which the co-occurrence of employee well-being and performance is studied through a person-centered approach (Ayala et al., 2017; Tordera et al., 2020). Moreover, as negative well-being indicators (e.g. exhaustion) have been largely neglected in person-centered research thus far (Benitez et al., 2019), the use case presented in this dissertation examined positive (i.e. vigor) and negative (i.e. exhaustion) well-being in combination with task performance. Secondly, this study answered the call of Benitez et al. (2019) to study the possible antecedents of employee well-being and performance profiles. Specifically, it investigated whether certain job design characteristics are related to specific well-being and performance profiles. This was the second contribution to the SHRM literature.

Challenge 3: How can people analytics departments benefit from a collaboration with academia?

Summary of the main findings

In order to be effective at people analytics, people analytics practitioners need a great variety of skills (Andersen, 2016; McCartney et al., 2020). However, people who have these skills are a rarity. Therefore, a lack of skills among people analytics practitioners is seen as a barrier towards people analytics effectiveness (Fernandez & Gallardo-Gallardo, 2021; McCartney et al., 2020). To (partially) solve this issue, a collaboration with academia has been suggested (e.g. Angrave et al., 2016; Cascio et al., 2019; Simón & Ferreiro, 2018). Therefore, chapter 6 discusses the benefits, tensions and ways to navigate through these tensions of a joint PhD trajectory. A total of six benefits were discussed. 1. Similar to other collaborative research (e.g. Shani et al., 2007), the joint PhD trajectory allowed relevant research to be conducted for both parties. 2. Thanks to the long-term collaboration, sufficient time and opportunity was available to identify and address real and pressing business needs. The identification of a good research topic, has been pinpointed by Guerci et al. (2019) as crucial for successful collaborative research. 3. It allowed an extended knowledge network to be created in which both parties benefited from each other's knowledge and network. This has been identified as a benefit in earlier research too (Guerci et al., 2019; Mirvis, 2007; Pasmore et al., 2007). 4. Follow-up in practice was a given for our research results, while this can normally be a challenge for academic research (Beer, 2020). 5. In line with Zhang et al. (2015), we were able to utilize company's existing data. 6. The joint PhD trajectory established a bond of deep trust between both parties, and the organization and university became preferred partners to each other. This notion is similar to one of the benefits described by Simón and Ferreiro (2018).

Next, five tensions and ways to navigate through them were discussed. First, in line with Pasmore et al. (2007) the difference in potential gains practitioners and scholars hope to achieve were highlighted. Second, limitations to the quality, accessibility, enrichment, and gathering of new data with the partner organization were discussed. Although these are not typically identified as challenges within the collaborative research literature, they are common issues among people analytics departments (Andersen, 2017; Fernandez & Gallardo-Gallardo, 2021; Minbaeva, 2018). Third, similar to other scholars (Guerci et al., 2019; Simón & Ferreiro, 2018), differences in the ways of working between the organization and university work were described. Fourth, the challenging political arena within an organization that affects scientific research was illustrated. Although there are warnings within the literature of how practitioners may collaborate with academics for political gains (Kieser & Leiner, 2012), this dissertation showed how the internal political arena within the organization could hinder the research itself. Finally, it is concluded that it takes time to get the required familiarity and credibility within the organization to design and execute academic research.

This latter is also in line with other scholars who have identified business acumen as critical skill for people analytics practitioners to have (e.g. Guenole et al., 2017; McCartney et al., 2020).

Theoretical contributions

The collaboration with academia is not undisputed within the (people analytics) literature. For example, Rasmussen and Ulrich (2015) warn that the different interests of academics and practitioners may undermine the value of people analytics projects. This is because "academics who went into industry led with a theory about what they had studied, not with questions about business challenges facing the company" (Rasmussen & Ulrich, 2015, p. 237). Similarly, academics generally warn for a loss of objectivity, relevancy and difference in interest when academics and practitioners collaborate (Guerci et al., 2019; Kilduff et al., 2011). To fill up the skill gap within people analytics (Fernandez & Gallardo-Gallardo, 2021; McCartney et al., 2020) in a way that is mutual beneficial for organizations and academics, it has been suggested to use so-called "boundary spawners" (Minbaeva, 2018; van der Togt & Rasmussen, 2017). Boundary spawners, such as PhD candidates, can bridge the gap between academia and a people analytics department (Minbaeva, 2018). To the best of my knowledge, an example of how a joint PhD trajectory may bridge this gap was still missing within the people analytics literature. Therefore, the concrete insights into the benefits and challenges within a joint PhD trajectory is the final contribution of this dissertation.

Points of reflection

After having answered the different sub-questions of this dissertation, I want to offer the reader with four theoretical reflections about use of people analytics based upon this dissertation and the practical experience that I gained by working in the field as a shared PhD. First, I will discuss how people analytics can contribute to and benefit from the other major trend within the HR domain: The employee experience (Dye et al., 2020). Second, I will argue how and why people analytics scholars can learn from the data and analyses techniques people analytics practitioners use. Third, despite the benefits of people analytics that I showed in this dissertation, there is a very dark side to people analytics. For example, companies also misuse people analytics to fire employees who are not being "productive" enough according to an algorithm (Business Internet Tech, 2021; Soper, 2021). As I believe both warnings and nuances are needed in this debate, I will pay attention to the role of ethics in people analytics below. Finally, I will spend attention to the governance of people analytics and specifically to the question who should govern people analytics analyses. This question is relevant because software developers of people analytics are increasingly enabling HR professionals and managers to conduct advanced people analytics analysis on their own (e.g. Lattice, n.d.; SplashBI, n.d.). However, considering

the amount of knowledge and skills required to conduct these analyses correctly (McCartney et al., 2020), I will raise some concerns about this development..

How can people analytics contribute to and benefit from the employee experience?

The employee experience (EX) is a relatively new concept that has emerged only a few years ago. Yet, according to recent research conducted by LinkedIn, 96% of the 9,000 participating HR professionals believe that it is becoming increasingly more important (Dye et al., 2020). The large interest in the employee experience also shows in the number of recently published books (e.g. Bridger & Gannaway, 2021; Morgan, 2017; Whitter, 2019), management articles (e.g. Armano, 2021; Emmett, Komm, Moritz, & Schultz, 2021) and companies that promise guidance on the topic (e.g. Culture Amp, n.d.; Gallop, n.d.; Qualtrics, n.d.). So what is the employee experience? Morgan (2017) defined the employee experience as "the intersection of employee expectations, needs, and wants and the organizational design of those expectation, needs, and wants" (p. 8). Plaskoff (2017) defines it more plainly by saying it is the "new Human Resource Management" that puts the total experience of an employee at their work at their center. Finally, Bersin (2020) states that it means that "we [HR professionals] work for the employees, and *not the other way around*". Regardless of the definition, the overall goal appears to be the same. To create a company where people want to work (Morgan, 2017). As every employee has different expectations, needs, and wants, this means that a personalized employee experience that is co-created together with the employee is needed (Whitter, 2019).

In order to understand what employee expectations, needs, and wants are, people analytics can be used (Bersin, 2020). This makes people analytics an enabler of the employee experience and the employee experience practitioner a stakeholder of a people analytics department. Considering that a good employee experience is seen as critical for the company's competitive advantage, it also seems a strategically important partner to the people analytics function (Bridger & Gannaway, 2021; Whitter, 2019). This is because the employee experience aims to attract the most talented people to the organization, offers a way to mitigate the stress employees experience from contextual factors (e.g. Covid-19) and, perhaps most importantly, aims to contribute to employee performance and well-being (Bridger & Gannaway, 2021). Therefore, the people analytics function can use the popularity of the employee experience by offering insights and recommendations valuable to enhance the employee experience and via this employee performance and well-being.

In my opinion, a people analytics function can support the employee experience in five ways. First, a people analytics function can provide insights into employees' expectations, wants and needs through varoius "employee listening" tools, such as employee surveys and qualitative research. Especially the type of topics the

employee experience typically focuses upon, like leadership, (HR) practices and the organizational climate (Shenoy & Uchil, 2018) are commonly present within the annual and pulse surveys organization use (Chapter 3). Therefore, it does not take much for a people analytics function to provide basic insights that could support the employee experience. This may be done through a dashboard that identifies leadership satisfaction trends or the comments collected via open questions in a survey. Using this information, employee experience experts may detect when employees' satisfaction drops or highlight relevant comments these experts need to act upon. With regards to qualitative research, most people analytics functions I investigated in chapter 3 did not conduct traditional qualitative research. Specifically, although they analyzed unstructured text data, they did not conduct interviews. However, a few companies did have experts on qualitative research working within people analytics. These experts could assist employee experience practitioners or conduct interviews themselves to collect in-depth insights on the employee experience when required.

Second, a people analytics function can also offer insights and recommendations about how a differentiating employee experience can be created for various types of employees. Bersin (2020) for example suggests that employee personas can help employee experience practitioners think about the wants, needs and expectations of different employee groups about rewards, development and career opportunities. This is similar to the study I conducted in chapter 5. Specifically, I used people analytics to identify different employee profiles, such as employees who experience high well-being and performance and employees who experience high well-being and low performance. Furthermore, it was found that employees with high well-being and low performance had less work pressure compared to those with high well-being and high performance. Therefore, these insights can inform employee experience practitioners how to differentiate the work environment for different well-being and performance profiles to increase the chances they transition to the most favorable employee well-being and performance profile (i.e. high employee well-being, top performance). In addition to the research design that I used, other methods such as group interviews or the Q-methodology can also be used. The latter seems especially suitable to me, as it aims to systematically study the subjective viewpoints of participants (Stenner, Watts, & Worrell, 2020) and can therefore analyze the wants and needs of a large (employee) population. In practice, this has also been demonstrated by for example the company Crunchr. They analyzed what different generations value in their job (e.g. high salary, compensation and benefits, flexibility) (van Gool, 2016). Employee experience practitioners may use these insights to provide a better work experience to different employees based upon their specific wants and needs.

Third, a people analytics function can also help the employee experience by designing new projects that aim to improve the so-called employee life cycle and identify the

moments that matter during this life cycle. The employee life cycle begins at the pre-hiring stage, after which the hiring, onboarding, development, and eventually the end of the contract follows (Gallop, n.d.; Morgan, 2017). Although employees can be subjected to general employee listening tools during these times (e.g. the annual and pulse surveys), listening initiatives may also be developed that focus upon these "moments that matter", such as onboarding or performance management conversations (Gallop, n.d.; Qualtrics, n.d.). Specifically, this implies that a people analytics function may develop surveys tailored to onboarding or systematically gather the data from exit interviews. This is also called event-based research. Following chapter 2 and 3, there are a great number of knowledge, skills, capabilities and other characteristics (KSAOs) required to design high-quality listening initiatives though. A people analytics department may support the employee experience by designing, for example, the onboarding survey and analyzing its results.

Fourth, event-based research can be coordinated by a people analytics function. This implies that the people analytics function evaluates all "moments that matter" from one central place within the organization and sends out surveys when appropriate. This has a number of benefits. For example, suppose a people analytics department ties event-based surveys to triggers within the HR information system (e.g. onboarding, performance management conversations, leaving). In that case, surveys will automatically be sent out when appropriate: If a new employee joins, he or she will automatically receive a survey based upon his or her starting date. Furthermore, as employees receive surveys when events happen, at least on paper, it means the surveys are at that moment most relevant to the employee. Therefore, the chances that the survey leads to increased levels of survey fatigue are smaller than if the survey was sent to the entire employee population (de Koning et al., 2021; Groves, Presser, & Dipko, 2004). Concerning the quality, event-based research reduces the chance of various memory biases affecting the results. These biases can occur, for example, due to respondents remembering an event incorrectly or remembering it more positively or negatively in hindsight (Levine, Lench, Karnaze, & Carlson, 2018). Therefore, it will likely improve the data quality when data is being gathered as specific events occur. All in all, having the people analytics team coordinate the evaluation of the employee experience, benefits the efficiency of the process, relevancy of the questionnaire to employees and quality of the insights.

Fifth, event-based research allows for the content as well as the research design to be tailored to the event itself. For example, for new joiners, I believe that multiple onboarding surveys with varying content that assess how an employee is experiencing their first day, week and month(s) would work best. This is because the experiences of a new hire may greatly fluctuate over time. For example, a new hire may feel great after meeting his or her new colleagues and supervisor on the first day at work. However, if the same employee does not receive access to all relevant systems within

a month after joining, this initial excitement may turn into disappointment. Therefore, it is important that multiple surveys track the employee's experience through his or her onboarding period to identify, in this specific case, that the IT systems harm the onboarding experience.

In sum, I thus believe that people analytics can help employee experience practitioners improve the employee experience in various ways. This contributes to their purpose of enhancing employee well-being and performance. Finally, I also believe that SHRM scholars, with their expertise in researching and designing HR practices, may provide employee experience and people analytics practitioners with valuable advice on how to go about this.

Intertwining data science with HR research

I have demonstrated how people analytics can provide insights and recommendations throughout this dissertation using my expertise as an SHRM scholar. As is common practice among SHRM scholars, I analyzed survey data within two chapters of this dissertation (Chapter 4 and 5), designed and validated a new survey, and analyzed the resulting data using factor analysis and structural equation modelling (Chapter 4). While the analyses methods I used in chapter 5 (latent class analyses and multinominal regression) are less common among SHRM scholars, they are increasingly used by them (e.g. Ayala et al., 2017; Bennett et al., 2016; Gabriel et al., 2019). I believe that relying upon my SHRM expertise was the most logical thing to do considering the situation. On the one hand, this is because the people analytics department I collaborated with initially lacked the theoretical knowledge and skills required to do these types of analyses on its own. On the other hand, the organization also had few other datasets available that were accessible, of sufficient quality and relevant for me to use for scientific research (Chapter 6). As a general note, however, I believe that SHRM scholars can learn much from data scientists who work within the people analytics domain. In reverse, I believe that data scientist-practitioners can also learn much from SHRM scholars. I will discuss why I believe this below.

For SHRM scholars, I, first of all, strongly recommend to utilize different data sources and extend their analyses repertoire with data science techniques. For example, many organizations are spending a lot of time analyzing unstructured (organic) data, such as text, video, audio, web server logs, and posts on social media (Harbert, 2021). Within people analytics, some of these are typically not used for ethical and privacy concerns (Giermindl et al., 2021), but there is much attention for analyzing text data using Natural Language Processing (NLP). Like this, they can determine, for example, the overall sentiment among their employees (i.e. positive, neutral, negative) or the specific topics they talk about (e.g. leadership, performance management, culture) (Ferrar & Green, 2021; Ledet et al., 2020). The primary benefits are that existing data can be analyzed (e.g. intranet data) and open questions can be asked

within surveys. The latter provides respondents more flexibility when answering a question. With NLP techniques, the data can also be processed reliably and efficiently (Wijngaards, Burger, & van Exel, 2019). However, with notable exceptions (e.g. Wijngaards, Burger, & van Exel, 2021), SHRM scholars have rarely utilized NLP to analyze unstructured data (Hickman, Thapa, Tay, Cao, & Srinivasan, 2020; Pandey & Pandey, 2019). As many practitioners are highly positive about the "highly actionable insights and recommendations" this provides (Ferrar & Green, 2021), I believe that SHRM scholars should join the debate and explore whether it may be beneficial for advancing scientific SHRM research too. For example, scholars may use NLP as an alternative to a questionnaire or use open questions to partially replace Likert-scales. As an alternative for a questionnaire, Pandey and Pandey (2019), measured, for instance, the organizational culture using NLP through existing text data (e.g. archival data, intranet posts). As their method was found to score high on validity, scholars may use pre-existing data as an alternative to collecting new data (Pandey & Pandey, 2019). Partially replacing Likert-scales with open questions may furthermore be a useful approach to shorten questionnaires used by academics. This is in line with the approach of, for example, ABN Amro who replaced their Likert-scale survey with a survey consisting of only three questions (1 numeric score question, 2 open questions) (Ferrar & Green, 2021). Practically, scholars may use open questions to uncover, for instance, what employees like about their job and relate this to employee outcomes measured through Likert-scales (e.g. engagement, performance). Through this method, scholars may be able to replicate, for example, the findings presented in chapter 5, but with a much shorter survey because the antecedents are derived from the open questions instead.

Aside from NLP, there are also other ways that SHRM scholars can benefit from data and techniques used in practice. For example, some practitioners do not rely on survey data. Instead, they only use HR Information System data or metadata from e-mail and other software packages. Recently, a study by Yang et al. (2021), for instance, demonstrated how data coming from e-mails, calendars, instant messages, video/audio calls and workweek hours of over 60,000 employees was used to investigate how employees communication and collaboration patterns switched as a result of working from home during the pandemic. To analyze this data, a difference-in-differences model was used. This model originates from econometry and compares longitudinal data from an experimental group to a control group. In this case, the "experimental" group, those who were forced to work from home due to the pandemic, was compared with the "control" group. The control group consisted of employees who were already frequently working from home prior to the pandemic. The results showed, among others, that firm-wide remote working caused employee collaboration patterns to become more static, siloed and with fewer bridging ties. In a different research, Gloor, Colladon, Grippa, and Giacomelli (2017) demonstrated, through e-mail data and social network analysis, how managers' communication

typically changed five months before they left the company. In my opinion, these studies illustrate two important things. First, there are many alternative datasets that SHRM scholars may use to make important contributions to the HR literature (Pandey & Pandey, 2019). Second, SHRM scholars may borrow analysis methods common to other fields. Nevertheless, research like this is still a rarity within the field (Hickman et al., 2020). Therefore, SHRM scholars may benefit from using the datasets and analysis methods common among data scientist-practitioners to advance the body of HR knowledge (Xu, Zhang, & Zhou, 2020).

There are three primary gains for data scientists by utilizing knowledge common to SHRM scholars when working within people analytics. First, while SHRM scholars seem to over-rely upon (subjective) survey data, data scientists seem to be hesitant about using it. This showed in data scientists' (initial) reluctance to work with survey data in the organization I worked at (Chapter 6), and in discussions with other practitioners. For example, although "HR analytics" and "people analytics" are seen as the same practice with a different label within the people analytics literature (Margherita, 2021; Qamar & Samad, 2021), I had discussions with practitioners who believed that one referred to the analysis of "subjective" survey data whereas the other referred to the analysis of "objective" data (e.g. HR Information System data). Others were surprised I used subjective data for people analytics projects at all. I believe that the hesitation in using subjective data is a missed opportunity because, unlike various other analytical sub-domains (e.g. finance and marketing analytics), human complexity is at the core of people analytics (Giermindl et al., 2021). This means that although objectively speaking happiness may, for example, be similar for two people, different aspects of happiness may weigh differently in someone's life. Consequently, Alexandrova (2005) argues that happiness needs to be judged subjectively by the person in question in order to identify the best action to take. Therefore, I believe that the insights and recommendations provided by people analytics are at their best when subjective and objective datasets are combined.

Second, data scientists can, in my opinion, benefit from using a more theory-driven approach. For chapter 5, for instance, I had much more data at my disposal than I ended up using. The survey central to this research, was tailored to according to the third party provider to (W. B. Schaufeli & Taris, 2014) measure the central concepts of the Job Demands Resource (JD-R) (Demerouti et al., 2001). However, many questions within the survey also addressed the physical work environment (e.g. lightning and noise at the workplace) and the person-job fit. Although these were all relevant factors too, I made the conscious decision to exclude them within my analysis. The rationale for this decision was twofold. On the one hand, it made the most sense to look at the job demands and resources that I included based upon the JD-R model and the extensive body of literature that studies it (Bakker & Demerouti, 2007; W. B. Schaufeli & Taris, 2014). On the other hand, I consciously limited the

number of variables in my model to ensure I would not find significant effects purely based upon chance which often happens when analyzing large datasets with many variables (Smith & Ebrahim, 2002). Therefore, my decision also reduced the chance of erroneous conclusions. Based on my practice experience, it does not seem common among data scientists to build a theoretically grounded conceptual model with clear hypotheses though. Therefore, data scientists would benefit from adopting this more theoretical approach common among behavioral scientists to reduce the chance on erroneous conclusions.

Third, regarding the methods and interpretation of the results, I believe that data scientists can also learn from SHRM scholars. As human behavior is more complex and less predictable than any other analytics-sub domain, the methods commonly used by data scientists may oversimplify the reality and cause misinterpretation, miscalculation and errors (Giermindl et al., 2021). For example, a 45-items survey used by the partner organization appeared to be of insufficient quality based upon research done by the research team (i.e. my two promotors and myself). Initially, the exploratory factor analysis showed that four factors were sufficient to summarize the data. However, upon closer inspection, it appeared that the items allocated to the four factors did not have a clear underlying topic from a theoretical perspective. Therefore, we ran a confirmatory factor analysis and found a one-factor solution more suitable for the data. Although data scientists had run an exploratory factor analysis on the same data, they did not evaluate the results from a theoretical perspective and did not discover the full extent of the problem. That was, that all items appeared to measure one generic employee satisfaction construct. As a result, it was only after the analyses conducted by the research team, that the survey was canceled within the partner organization (Chapter 6). As it is equally important for other analyses techniques commonly used within the HR domain to evaluate the results on theoretical grounds, it is important data scientists evaluate their results on theoretical grounds too.

Based upon the previous, it can thus be argued that SHRM scholars and data scientist-practitioners can learn from each other to produce high-quality practical and scientific insights and recommendations for their respective audiences.

Ethics within people analytics

Within chapters 2 and 3 of this dissertation, I have paid attention to the role of ethics in people analytics. This is important because there are numerous examples of how people analytics can harm employees. A number of these, like identifying underperformance and firing employees solely based upon the recommendations provided by people analytics, have been discussed already within the introduction of this dissertation (Business Internet Tech, 2021; Ramishah Maruf, 2021; Soper, 2021). However, many other questionable practices are happening within the people

analytics domain. For example, some organizations create personality profiles for applicants based on their social media posts (Hamilton & Davison, 2021; Vollebregt, 2021). Others use it to intrusively track and shape employee behavior (e.g. nudging certain employees to eat healthier snacks) (Tursunbayeva et al., 2021). Again others, use it to monitor their employees 24/7 and track, for instance, employees' location (cellphone GPS), activity (fitness trackers), and social media regardless of whether they are at work or not (Ajunwa, Crawford, & Schultz, 2017). Additionally, people analytics can also lead to more subtle and even unintentional unethical effects. For instance, although Amazon's hiring algorithm discriminated against women, it was never the organization's intention for it to do so. However, because the organization had primarily hired males in the past, the algorithm simply learned that being male was an indicator of a successful employee (Dastin, 2018). In the same way, Hamilton and Davison (2021) warn that an algorithm may unintentionally learn to discriminate against minorities, older workers, or people with a disability. This is because any potential discrimination in the past will be discovered by an algorithm, learned, and amplified because an algorithm has no ethical compass.

Despite these examples, the majority of the literature on people analytics focuses on the potential benefits of people analytics and still neglects its ethical challenges (Giermindl et al., 2021). In response, several recent articles highlight the ethical side of people analytics (e.g. Giermindl et al., 2021; Hamilton & Davison, 2021; Tursunbayeva et al., 2021). Their main message seems to be that despite the improved laws on the use of employee data, there is still a real need to think about the ethical side of people analytics (Tursunbayeva et al., 2021). The reason for their warning, is that many projects will be legally allowed as long as the organization can argue that there is a legitimate business purpose for gathering and analyzing this data. This is even the case under the GDPR in Europe, despite that this is argued to be the most strict legalization regarding employee data (Hamilton & Davison, 2021).

The sentiment that it is insufficient only to follow the law, was also present among many of the people analytics practitioners I interviewed for chapter 3. Moreover, they mentioned that behaving unethically is not in the best interest of the people analytics function either. There are three main reasons for this. First, mistrust among employees can result in poor data quality for the people analytics function (e.g. employees filling out their survey untruthfully) (Chatterjee, Chaudhuri, Vrontis, & Siachou, 2021; Falletta & Combs, 2021). Second, it can make highly employable employees leave or scare away potential hirers (Chapter 3). Third, ethical scandals can harm the company's reputation and affects its financial performance (Hamilton & Davison, 2021). As a result some companies, became high-risk averse regarding people analytics, according to a number of interviewees I spoke with for chapter 3. I also experienced this myself, as I had to go through a complex and lengthy procedure to

acquire or collect a certain dataset and was denied access to certain data altogether (Chapter 6).

However, while I believe it is important to be mindful of compliancy and the ethical use of employee data, I also believe that some organizations seem to forget that single-mindedly focusing upon protecting employee data, may have adverse effects for the employees. For example, for chapter 4, I was initially unable to deliver actionable insights to the participating agile teams. This was because the reporting threshold of all people analytics reports was set to 10. However, the agile teams I studied typically consisted of five to nine members. Thanks to good discussions with Data Privacy Officers in the partner organization, I was able to lower the reporting threshold to 5 and provided many teams with their own aggregated team scores. In contrast, team managers did not receive these team reports automatically to provide employees with additional control of their data. Therefore, managers were dependent upon the willingness of their employees to share the team report with them. This example shows that it is sometimes in the employee's interest to review the procedures once more and consider the potential benefits of conducting people analytics. In the remainder of this section, I therefore want to focus upon three examples of where I believe it is ethical to push for people analytics.

First, as I highlighted with examples in the introduction, people analytics can bring more equality and fairness to the workplace. For example, people analytics can provide insight into a potential gender pay gap (Coron, 2021), identify talents within the organization that may otherwise stay under the radar, and support hiring decisions (Logg, 2019). The word "support" is key here, as I believe algorithms cannot and should not replace managers (Giermindl et al., 2021). This is because biases may enter an algorithm unknowingly (Hamilton & Davison, 2021), 'human' managers are important for the employees (e.g. for real interaction, help and feedback) (Giermindl et al., 2021), and negative side effects can occur if a human is no longer involved in the decision. Keding (2021), for example, notes that recipients of the decisions may not accept nor trust a decision taken by an algorithm alone. On the other hand, Bader and Kaiser (2019) point out that employees may become detached and lower their performance if the balance between human and algorithmic involvement in the decision-making process is lost. In practice, algorithms are therefore best to support employees by, for instance, completing routine tasks (e.g. administration) so that employees have more time to engage in meaningful tasks (Keding, 2021). Furthermore, they may also be used to shift through a large amount of data. Kuncel et al. (2013), for example, argue that algorithms may be helpful to shift through a large number of resumes and recommend a small number of candidates to the hiring manager. Because the latter means that candidates were recommended based upon objective grounds, at least if the algorithm is built correctly, this saves the hiring manager time, and increases the chances of fair hiring decisions (Logg, 2019). This

is because the manager may invite candidates for a selection interview, which he or she may have initially not considered due to his or her own biases. All in all, if attention is paid to the limitations, people analytics can thus be used to create a more meaningful work experience for employees and promote equality and fairness in the decision-making process.

Second, people analytics can be used to increase the employability of employees. On the one hand, people analytics can, for example, be used to show which future career options make sense for a specific employee based upon the career paths of others in the future. Using this, an employee can receive tailored recommendations on how he or she may develop him- or herself in preparation for the aspired job. On the other hand, this also provides transparency to employees who do not have the skills (yet) crucial to the organization in the future. Therefore, a potential situation in which the employee becomes redundant in the future may be prevented (Rosenbaum, 2019), which means the employee remains employable.

Third, as demonstrated in chapters 4 and 5, people analytics can also provide insight into employee well-being. However, well-being data, especially those health-related, are highly sensitive. Although I agree that it should be carefully considered whether there is a need for this data, organizations also have a moral and legal obligation to take care of their employees. Therefore, they must consider, for example, the safety of the workplace and prevent long-term absenteeism of their employees to the best of their abilities (European Agency for Safety and Health at Work, n.d.). As people analytics can identify the specific areas in which workplace accidents are more common or work-related causes of long-term absenteeism. It can thus also be argued that organizations are obliged to use people analytics as an instrument to improve employee well-being. Therefore, I believe that analyses on employee well-being should be possible as long as there is a legitimate purpose and misuse is prevented by design (e.g. only reporting aggregated findings to management).

In conclusion, I believe people analytics can be greatly harmful and beneficial to employees. In line with the utilitarianism view on ethics, all parties' expected net gains should be considered before any people analytics project is started (Herschel & Miori, 2017). Suppose, for instance, a project is expected to result in results that help employees and the organization, and it aligns with the ethical compass of the people analytics experts and its primary stakeholders, it should be possible to do the project even if it uses (highly) sensitive data. However, it will always be essential to evaluate whether a specific people analytics project is ethical, because there is the potential to do more harm than good (Giermindl et al., 2021; Hamilton & Davison, 2021; Herschel & Miori, 2017; Tursunbayeva et al., 2021). Practically, organizations may therefore create procedures or establish an ethical board that evaluates for each people analytics project whether it is ethically just to execute or not.

Organizing people analytics (governance)

Following chapters 2 and 3, this dissertation has discussed the governance of a people analytics function in multiple ways. For example, it reflected on the position of the people analytics department within the organization (e.g. within HR or the broader analytics domain). In addition, it discussed how the department should be structured (e.g. in multiple sub-teams or a large team). Finally, it considered how work should be distributed within the department (e.g. split between different functional profiles or owned by an all-round individual). However, as the people analytics software that firms are using is becoming increasingly more advanced, I believe that people analytics departments and scholars should also focus upon another question. That is, who should own people analytics?

I believe it is important to answer this question, because people analytics software providers are currently at a stage where they can help their users "delve deeper into the behavioral aspects of work and make better business decisions" (Techfunnel, 2021). One such provider, SplashBI allows customers to "use predictive analytics to identify high performing employees who are flight risks" (SplashBI, n.d.). Similarly, Lattice promises insights into the drivers (i.e. antecedents) of business outcomes like engagement and performance (Lattice, n.d.). These software packages provide easy access of people analytics insights and recommendations to business executives, HR practitioners, and line managers. On the flip side, this enables the people analytics department to provide insights and recommendations to decision-makers (Ellmer & Reichel, 2021). However, it is a question of whether decision-makers should be able to conduct (semi) automated advanced analytics without any governance by the people analytics department.

The problem with the (semi) automated advanced analytics is, that it is likely to result into errors in the hands of decision-makers. This is the case for three reasons. First, managers and HR professionals typically lack the knowledge and skills to conduct advanced people analytics and may misinterpret the outcomes as a result (Giermindl et al., 2021; McCartney et al., 2020). Consequently, they may end up taking the wrong actions and waste valuable organizational resources (Giermindl et al., 2021; Leicht-Deobald et al., 2019). Second, all advanced analytics techniques have an error margin. Typically, HR scholars and people analytics practitioners use an error margin of 5%, which means their conclusions will be wrong five out of a hundred times. However, decision-makers who use these people analytics software packages may be unaware of this error margin and follow the results without second-guessing them. Third, because these software packages are easy to use, decision-makers may attempt to run multiple analyses simply because they can and are curious. However, they (unknowingly) "fish" for statistically significant effects and will also find them. This is problematic, as not all significant relations that these decision-makers will find will be cause and effect relations. For example, there is also a strong relationship between

the number of people drowned by falling into a swimming pool and the number of movies Nicolas Cage appeared in (r = .66) (Vigen, n.d.). Luckily for the actor though, this is an example of a spurious relationship in which another (still unknown) variable explains this relationship. Similarly, it is important to be critical about the statistical analysis results and have a hypothesis in place before any analysis is conducted to reduce the chances of drawing the wrong conclusions. However, because it is easy to conduct these analyses and its users did not receive proper training, it is unlikely that all decision-makers will follow this approach.

Following the previous, I believe that the extent to which decision-makers should be able to conduct advanced people analytics analysis themselves should be carefully considered. This has not been an issue in the past, as software packages only offered basic and straightforward insights (e.g. seeing how many people left their department this year and predicting the number of new joiners in the coming year). However, as the complexity of the analyses within these packages increases, it becomes increasingly important to think about their governance. My standpoint is that I believe that advanced people analytics should not be conducted by those who are not trained for it as the risk of errors and wasting resources on the wrong actions is too great. However, I also believe HR scholars and people analytics departments should consider developing the required skills among decision-makers and find ways in which the insights and recommendations of a people analytics department are accessible beyond, typically, a very select group of senior stakeholders (Chapter 2). This can be done by building the capabilities of stakeholders through, for instance, trainings, workshops, internships of formal (executive) training programs.

Strengths and limitations

This dissertation has a number of strengths and limitations that should be considered when interpreting the results. First, due to the collaboration between the company and Tilburg University, I experienced firsthand how an effective people analytics department might look like. Moreover, I was also able to interact informally with many people analytics practitioners from within and outside of this department and learn their opinions. However, it cannot be ruled out that I unconsciously sought to confirm my own expectations of what an effective people analytics function may look like based upon this experience. Therefore, this dissertation may have been subject to confirmation bias. To alleviate this concern, multiple actions were taken. Following the recommendation of Guerci et al. (2019) I functioned as a bridging mechanism between Tilburg University and the partner organization. This meant that my co-authors were able to keep their autonomy and rigor while working on these collaborative research projects. Furthermore, in line with Nickerson (1998) the literature and the interviews (transcripts) were openly explored to identify any emerging themes from the data. We started each data analysis with a blank sheet and added the elements a people

analytics function requires based upon our findings. Finally, for chapter 3, data from various companies, countries and sectors was gathered to limit the potential effects of confirmation bias further. Nevertheless, it is recommended to test the propositions that we developed through large scale, longitudinal survey research. On the one hand, this research can verify the conclusions among a broader range of companies and assess how a people analytics function develops over time. The latter can also help to uncover additional elements that are related to a successful internalization of people analytics. On the other hand, this research can also help develop the empirically grounded framework presented in chapter 3.

Second, the use cases displayed within this dissertation have been conducted within the same company. As the research team was able to collaborate with the organization for a longer period, it developed an in-depth understanding of the organization. This is seen as a critical competency within people analytics, as it allows individuals to ask the relevant business question and address those topics that matter (Andersen, 2016; Guenole et al., 2017). As a result, both use cases resulted in relevant insights for the partner organization and a new scientifically validated survey tool that can be used for agile teams (Chapter 4, 5 and 6). However, the context within the organization and its strategic priorities affected the type of use cases presented within this dissertation. Therefore, other companies likely want to use people analytics in different ways. For example, whereas this company viewed the agile way of working as pivotal to its competitive advantage, other companies may be more interested in reducing work-related accidents or dealing with its aging workforce. As such, this dissertation provided only a glimpse into the possibilities for using people analytics, and future research is needed to demonstrate other people analytics use cases.

Third, data from a single company, from a single source and at a single point in time was used for chapter 4 and 5. On the plus side, these were large, highly contextualized datasets that included respondents from many functional areas (e.g. IT, HR, legal, customer serves etc.). This meant that the use cases provided generalizable, tailored insights to the organization in question. However, this does mean that the results may not apply to other organizations and that common method bias may have occurred. Although, this did not appear to greatly affect our results based upon techniques that checked for common-method bias (P. M. Podsakoff et al., 2003), I recommend scholars to conduct similar research in other sectors, collect longitudinal datasets and consider other data sources. In line with the recommendations provided in chapter 4, other scholars may, for example, gather data from the "scrum board" or observe agile team interactions when studying agile teams. For the study on performance and well-being profiles, data from other raters (e.g. managers, colleagues) or text data may prove useful. Regarding the latter, topic analysis using natural language programming may, for example, be used to disentangle antecedents of different well-being and performance profiles.

Fourth, chapter 6 has been written solely upon my own experience. On one hand, this allowed me to demonstrate the specific benefits, challenges and results of this collaboration for our partnership. On the other hand, this experience is not generalizable beyond this partnership. Therefore, future research is required that demonstrates how organizations and practitioners may collaborate on people analytics. Furthermore, as this is to the best of my knowledge the first time a bridging mechanism is tested within the context of people analytics, the added value of bridging mechanisms, like shared PhD programs, MBA's and socialization events and meetings needs to be assessed among a variety of partnerships (Guerci et al., 2019).

Fifth, advanced people analytics departments seem typically located within large multinationals (Ferrar & Green, 2021). Because of the relatively high amount of immature people analytics departments within the field (Ledet et al., 2020), all data, except chapter 2, was collected in multinationals. Therefore, the results may be less applicable to smaller companies because they may for example lack the resources to establish a (large) people analytics department. Now that people analytics is becoming more accessible thanks to people analytics software (Techfunnel, 2021), future research should address what elements small, medium and large-sized companies need to benefit from people analytics. Furthermore, it should be investigated whether the same benefits and challenges apply when they would collaborate with academia.

Practical implications

This dissertation has a number of practical implications. First, it identified the elements a people analytics function requires to be effective and provided practitioners with some clear, scientifically validated guidelines to set up and advance their own people analytics function. Practitioners can use these insights to manage elements within the people analytics function (e.g. data, KSAOs), its context (e.g. senior management support, culture) and processes they can use (e.g. project management, stakeholder collaborations) to produce direct (e.g. insights and recommendations) and indirect outputs (e.g. analytical capabilities) required to enhance business outcomes. Furthermore, it showed that these indirect outcomes, in turn, affect the future context and the function itself through a feedback loop. The latter implies that a people analytics function will likely gradually improve over time. This was also illustrated in chapter 6, which showed that it took our partner organization several years to become truly effective at people analytics. Considering that many organizations have yet to get started with people analytics despite their interest (Ledet et al., 2020; Orgvue, 2019; Sierra-Cedar Inc., 2019), it seems important that they start their people analytics journey as soon as possible. After the initial start, practitioners can gradually improve the elements identified in this dissertation to establish an effective people analytics function.

Second, this dissertation illustrated that people analytics can provide insights and recommendations to enhance employee well-being and performance in line with the multiple stakeholder perspective (Beer et al., 2015; Guest, 2017; Paauwe & Farndale, 2017). Specifically, it illustrated how people analytics may be used to evaluate a strategic decision of a company (i.e. to implement the agile way of working, chapter 4) and showed how it can provide insights in support of job design (e.g. by studying employee well-being profiles and their antecedents). There is a scarcity of empirical examples in the people analytics literature that demonstrate how people analytics may support employee well-being and performance in conjunction (Fernandez & Gallardo-Gallardo, 2021; Margherita, 2021; Qamar & Samad, 2021). This is problematic because what is good for employee well-being, is not necessarily good for their performance and vice versa (Peccei & van de Voorde, 2019; Peccei et al., 2013). Considering that the multi-stakeholder perspective is gaining momentum globally (Beer et al., 2015; Guest, 2017; Paauwe & Farndale, 2017), practitioners can benefit through this dissertation from two practical examples of projects that focus on managerial and employee interest through this dissertation.

Third, in line with other studies (e.g. Greasley & Thomas, 2020; Guenole & Feinzig, 2018) the findings of chapter 3 showed that many HR practitioners are skeptical about using people analytics or are confused about its benefits. Furthermore, whereas others may be enthusiastic about people analytics, only few managed to use the insights and recommendations strategically. This is disappointing, because people analytics can lead to important insights and recommendation for HR stakeholders as the previous paragraph showed. According to the interviewees (Chapter 3), one of the primary reasons why HR practitioners do not make use of people analytics effectively, is because they lack the required analytical capability. As a result, organizations may decide to engage into building the analytical capabilities of their HR practitioners. For all the organizations involved in our research (Chapter 3), this was also what happened in practice. Specifically, these people analytics departments actively built the capabilities of their (HR) stakeholders through for example trainings and on-the-job learning. However, HR practitioners may also consider educating themselves. There are, for instance, various master classes, executive trainings and even free online trainings (e.g. Datacamp) that can help HR practitioners increase their analytical capabilities. This can, considering the relevant insights and recommendations people analytics can provide (Chapter 4 and 5), help the HR function become more strategic and better equipped to enhance employee well-being and performance.

Fourth, this dissertation illustrated that it is important for people analytics practitioners to be aware of, and keep up to date with, the scientific HR literature. On one hand, this allows people analytics practitioners to build theoretically grounded models that are important for designing and analyzing a research project. This method may, for instance, ensure that the relevant research topics are considered in a project

and lower the chance to draw erroneous conclusion as a result of chance (see also "intertwining data science and HR research" earlier in this discussion). On the other hand, it can also inspire people analytics practitioners and provide practical guidance. Chapter 5, for instance, was inspired by the latest developments within the SHRM research (Peccei & van de Voorde, 2019) and the recent research on different well-being and performance profiles (e.g. Benitez et al., 2019; Tordera et al., 2020). As the results showed that employees may indeed have complex, profiles in which there is a trade-off between employee well-being and performance, the research had important implications for the job design within the organization. With regards to practical guidance, people analytics practitioners can use academic insights to improve their work. For example, various organizations are currently using, organic data such as intranet posts, as input for their people analytics projects (see again the "intertwining data science with HR research" section). However, these are not undisputed as scholars are concerned with the validity of the design and outcomes of these projects (Boegershausen, Borah, Datta, & Stephen, 2021; Xu et al., 2020). As potential solutions are also typically discussed in these articles, it is for multiple reasons important that people analytics practitioners are aware and up to date with scientific (HR) research.

Finally, this dissertation showed that business acumen is indeed necessary for a successful and effective collaboration between academia and practice (Chapter 6). Specifically, the joint PhD trajectory provided the research team with sufficient time to build up this business acumen and focus upon relevant people analytics projects for both parties. More generally, this dissertation illustrated how one of the proposed mechanisms to bridge the academic–practitioner gap, may work out in practice (Guerci et al., 2019; Minbaeva, 2018; van der Togt & Rasmussen, 2017). By describing the benefits, challenges and ways to navigate through these challenges of our joint PhD trajectory, this dissertation provides practitioners with practical insights and guidance on collaborating with academia to enhance their people analytics' effectiveness. Therefore, practitioners may use this dissertation to make an informed choice about whether such a collaboration may be useful to them.

Conclusion

Overall, this dissertation explored how people analytics can be used to gain insights into and provide recommendations to enhance business outcomes. To this end, it described what a people analytics function requires to be effective, investigated two potential use cases and showed how collaborating with academics may be beneficial and challenging. However, as the age of people analytics is just beginning, continued attention from academics and practitioners will be needed to ensure that the right bridges are built between different worlds to be effective at people analytics: These are the worlds of HR and technology; the worlds of academia and practice; the worlds of data science practitioners and HR practitioners; the worlds of subjectivity and objectivity; and the worlds of employee well-being and performance.

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Summary

Summary

Sparked by an ever-increasing amount of data, organizations have begun to analyze the data of their workforce in hopes of improving their business outcomes (Cascio, Boudreau, & Fink, 2019; Levenson, 2005). This practice is called people analytics and refers to "the analysis of employee and workforce data to reveal insights and provide recommendations to improve business outcomes" (Ferrar & Green, 2021). People analytics can support any employee-related decision (Ellmer & Reichel, 2021; Huselid & Minbaeva, 2019), help the Human Resources Management (HRM) function become more strategic (Angrave, Charlwood, Kirkpatrick, Lawrence, & Stuart, 2016), and allow an organization to prepare for the future (Guenole, Ferrar, & Feinzig, 2017). Practically, people analytics can, for example, identify internal and external talents, create succession pipelines, predict which talents may be tempted to leave the organization and provide recommendations on how they may be retained most efficiently (Minbaeva & Vardi, 2018; Rosenbaum, 2019; Yuan, Kroon, & Kramer, 2021). Due to these proposed benefits, organizations invest heavily in people analytics (Ledet, McNulty, Morales, & Shandell, 2021). Nevertheless, most organizations struggle to use it effectively (Ledet et al., 2020; Orgvue, 2019; Inc. Sierra-Cedar, 2019). Therefore, this dissertation aims to answer the following research question:

> *How people analytics can be used to gain insights into and provide recommendations to enhance business outcomes?*

To answer this question, this dissertation addressed three challenges from the people analytics literature after a general introduction of the topic and challenges in chapter 1. The challenges, their importance and the results of the different chapters are briefly discussed in the following.

How can an effective people analytics function be created? (challenge 1)
This dissertation investigates what a people analytics function requires to be effective. This is important, as there is a rather limited understanding of how people analytics can be implemented effectively within the people analytics literature (Fernandez & Gallardo-Gallardo, 2020; Qamar & Samad, 2021). To address this issue, I conducted a narrative literature review (chapter 2) and follow-up qualitative research (chapter 3). For the literature review, the people analytics literature and broader more advanced, business intelligence domain that people analytics is part of (Davenport & Harris, 2017; Holsapple et al., 2014) were investigated. Based upon this, a number of crucial elements for an effective people analytics function were identified. However, a number of gaps within the literature were also found. Specifically, the relationships between the different elements and the processes a people analytics function requires to transform its inputs into outputs remained unclear.

To address these gaps in our knowledge, qualitative follow-up research was conducted (chapter 3). To this end, 36 in-depth interviews with members of nine people analytics functions and their stakeholders were conducted. Based on the findings, eight processes were identified to transform the inputs into outputs. Some of these are related to the projects of a people analytics function (i.e. project selection, management, execution and the compliant and ethical behavior of people analytics experts) and others to their stakeholders (i.e. the attitude of stakeholders, collaborations, partnerships and the transparency of people analytics function to their stakeholders). Furthermore, the "People Analytics Effectiveness Model" together with seven propositions to guide future research were developed. These propositions illustrated on one hand the relative importance of the different elements a people analytics function requires. For example, having data was found to be more crucial than a specific organizational culture. On the other hand, the propositions showed the relationships between the different elements: Delivering high-quality people analytics products, for instance, increased the reputation of the people analytics function. Furthermore, as the reputation increased, people analytics functions were typically provided with more inputs and better contextual factors, such as access to new datasets and increased support from senior management.

How can people analytics be used to enhance employee well-being and performance? (challenge 2)

This dissertation demonstrates how people analytics can be used to enhance employee well-being and performance through two use cases. This is relevant, as organizations increasingly consider how the interest of the manager and employees may be achieved in conjunction (Battilana, Obloj, Pache, & Sengul, 2020; Paauwe, 2004). However, there are few empirical studies on people analytics that demonstrate it can provide insights and recommendations that support employee well-being or performance (Margherita, 2021). In chapter 4, I therefore demonstrate how people analytics can be used to evaluate whether the decision of a company to adopt the agile way of working is beneficial to employee well-being and performance. The agile way of working is an increasingly popular way of working among teams, that is characterized by self-management, face-to-face communication, reflexivity, a quick product turnaround and customer interaction (Beck et al., 2001). To do this, I developed a survey focused on the agile way of working and tested among 97 teams from an organization whether the agile way of working leads to beneficial outcomes. Based upon the results, it appeared that this was indeed the case: The agile way of working was found to be related to increased levels of team engagement and performance regardless of teams' functional domains. Moreover, it was found that these effects are partially mediated by psychological safety climate. Following this research, the company central to this research now has data-driven insights that support the decision to implement the agile way of working across a variety of functional domains.

In chapter 5, I show how people analytics can be used to provide insights about employee well-being and performance and inform job design practices. Specifically, I tested in line with the HRM literature (e.g. Ayala et al., 2017; Benitez et al., 2019; Tordera et al., 2020) whether complex trade-off patterns may occur between employee well-being and performance. Based upon data of 5,729 employees working in a large financial organization, I find support for the notion that five well-being and performance profiles exist: 1. Low well-being/low performance, 2. low well-being/medium performance, 3. high well-being/medium performance, 4. high well-being/high performance, and 5. high well-being/top performance. Furthermore, it appeared that specific job demands and resources are related to these well-being and performance profiles. Specifically, employees with more learning and development opportunities, more social support from colleagues, more autonomy, and less role-conflict were related to the high well-being profiles. Additionally, employees with more role clarity, more performance feedback, more autonomy, and less work pressure were related to the high- and top-performance profiles. Finally, communication and social support from the manager were found to be relatively weak antecedents of the different profiles.

How can people analytics departments benefit from a collaboration with academia? (challenge 3)

The final challenge this dissertation addresses is how people analytics departments may benefit from a collaboration with academia. This is an important topic, as a competency gap among people analytics practitioners has been identified as being one of the main obstacles for organizations to use people analytics effectively (Fernandez & Gallardo-Gallardo, 2020; McCartney et al., 2020). Specifically, Human Resource (HR) professionals usually fall short of statistical skills and statistically strong individuals usually lack business acumen and HR knowledge (Andersen, 2016; McCartney et al., 2020; Rasmussen & Ulrich, 2015). As a potential solution, a collaboration with academia has been suggested (Simón & Ferreiro, 2018; Van der Togt & Rasmussen, 2017). Specifically, the so-called "boundary spawners", in which for example PhD candidates bridge the gap between academia and a people analytics department is frequently mentioned within the people analytics literature (Minbaeva, 2018; Van der Togt & Rasmussen, 2017). To illustrate how this may work in practice, chapter 6 of this dissertation discusses the benefits, challenges and potential ways to navigate through these challenges based upon my own experience of working in a joined PhD trajectory for 4.5 years. In total, six benefits and five challenges were identified in this chapter. Among the benefits, the opportunity to conduct relevant research for both parties and the time and opportunity to identify and address real and pressing business needs are for instance discussed. With regards to the challenges, topics such as the different potential interest for both parties and limitations regarding the data are described.

Discussion

After addressing the challenges, the discussion follows in chapter 7. This chapter holds a summary of the main findings of this dissertation, their theoretical and practical contributions, strengths and limitations and points of reflection. The primary contribution of this dissertation is to explore how people analytics can be used to gain insights into and provide recommendations to enhance business outcomes. To this end, the discussion chapter described what a people analytics function requires to be effective, investigated two potential use cases and showed how a collaboration with academics may be beneficial and challenging. Furthermore, four points of reflection are discussed within this chapter. First, I describe how people analytics can contribute to and benefit from the employee experience. The employee experience is one of the actual trends within the field of HRM and emphasizes that organizations need to consider the wants, needs and expectations of their employees from the moment of their recruitment all the way to the moment they leave the organization. Furthermore, as each employee is different, employee experience experts emphasize the need to offer a differentiating employee experience depending on the wants, needs and expectations of specific employees (Dye et al., 2020; Whitter, 2019). In this section, five concrete ways in which people analytics can support employee experience experts through data-driven insight are discussed. Furthermore, the reverse value of the employee experience for people analytics is also discussed. Specifically, whereas a substantial amount of HR professionals are confused or skeptical about the use of people analytics (Guenole & Feinzig, 2018), the far majority is enthousiastic about improving the employee experience (Dye et al., 2020). By offering insights and recommendations on a topic HR professionals are enthousiastic about, it is suggested people analytics can improve the number of data-driven decisions taken within the HRM function, and through this, enhance employee well-being and performance.

Second, I explore how data science and HRM research can become more intertwined. On one hand, it is discussed how HRM scholars can utilize the data sources and analysis techniques used by data scientists to make new contributions to the HRM literature. Specifically, the analysis of non-survey data, such as unstructured text and (HRM) system data, is highlighted as a method to unveil relevant insights into the sentiment, behavior, and perceptions of employees (e.g., Gloor et al., 2017; Yang et al., 2021). On the other hand, it is suggested that data scientists may benefit more from using survey data, theories, and analysis and interpretation techniques common among HRM scholars. This could help them to avoid oversimplifying reality (e.g., human beings are more complex and unpredictable than the numbers captured in the HR information system or their model output may suggest) and avoid misinterpretations, miscalculations and errors as a result (Giermindl et al., 2021).

Third, I discuss the topic of ethics within people analytics. Despite of the benefits of people analytics that this dissertation highlighted, people analytics has also been used by organizations for unethical matters, such as intrusively tracking employees (Ajunwa et al., 2017; Tursunbayeva et al., 2021), (unintentionally) discrimination (Dastin, 2018) or even firing employees (e.g., Business Internet Tech, 2021). Therefore, the ethical aspect of people analytics are highlighted in this section. On one side of the spectrum, I discuss that it is always necessary to operate within the boundaries of the law but not always sufficient, and explore the negative consequences of behaving unethically for the people analytics function itself. On the other end of the spectrum, I also discuss three examples in which I believe it is ethically just to push for the use of people analytics. Specifically, I advocate that data-driven insights can bring more equality and fairness to the workplace, increase the employability of employees and enhance employee well-being. Therefore, it is concluded in this section people analytics is not necessarly good or evil and that it should be reviewed on a case-by-case basis whether it is ethical to use people analytics.

Fourth, I discuss the governance of people analytics. Although in this dissertation various governance aspects are discussed (e.g., data governance, governance of the people analytics function), I suggest people analytics scholars and practitioners should also pay attention to the question of who owns people analytics. This is important, as software providers are increasingly facilitating HR experts and line managers to run their own (semi) automated advanced analytics models. However, as these professionals typically lack the skills, there is a high risk of misinterpretation of the results, finding incorrect findings due to pure chance (e.g., as a result of the error margin for all statistical models) and statistical artifacts such as reverse causal relationships and spurious effects. I therefore recommend caution in enabling professionals who lack the capabilities to run advanced analytical models in fear of wasting valuable organizational resources on the wrong actions, and to focus on building their analytical capability first.

Finally, I conclude this dissertation by emphasizing that the age of people analytics is just beginning. Continued attention from academics and practitioners will therefore be needed to ensure that the right bridges are built between different worlds to be effective at people analytics: These are the worlds of HRM and technology; the worlds of academia and practice; the worlds of data science practitioners and HR practitioners; the worlds of subjectivity and objectivity; and the worlds of employee well-being and performance.

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Appendices

Topic guide (chapter 3)

Acknowledgements (Dankwoord)

Topic guide (chapter 3)

Introduction:
Introduction to research, consent, anonymity
Personnel introduction

People Analytics (mechanisms I):
Experience with People Analytics
Successful project
What
Where

Outputs: *(general)*
Tools to monitor employee well-being and performance
Supporting people related business decisions
Establishment of an evidence based culture

Mechanisms II: *(linked to successful project)*
HR professionals
Line managers
Unions and employee representatives
Other analytical teams

Inputs I: *(linked to successful project)*
People
Equipment
IT infrastructure
Financial resources
Top management

Inputs II:
Internal governance (team structure)
Data governance
External governance

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