Data-Driven Human Resource Management

The rise of people analytics and its application to expatriate management

Paul A. van der Laken

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Contents

1 Introduction

Contemporary organizations often include a Human Resource Management (HRM) department, which function it is to design and champion the policies and practices with which employees are managed and organized. Research has shown that organizations that are effective and/or efficient in their HRM processes (e.g., selection, training) can gain a competitive advantage (e.g., Wright, McMahan, & McWilliams, 1994). However, how do you find out which HRM policies and practices are effective and efficient in a specific organizational context? In practice, scientific findings are increasingly consulted as a basis of evidence for effective HRM implementation. However, such external evidence provides no guarantee of impact in the own, internal context. Hence, there is a strong need for organization-specific HR metrics and analytics to uncover which HRM practices and policies work and work best. Technological developments over the past years allow contemporary organizations to collect and analyze increasing amounts of data. Are these data already leveraged analytically within the HRM domain? How and where can HRM departments start with data analytics? And what kind of actionable insights can be retrieved from HRM data? These are some of the questions this dissertation explores.

This introduction will first discuss a short history of strategic HRM research alongside the increasing demand for evidence-based HRM. Next, it explores the rise of people analytics: what does it entail and how does it contribute to the basis of evidence for HRM. This introduction concludes with an outline of the research questions and the chapters of this dissertation. Moreover, the case of expatriate management is presented, which we will approach from a people analytics perspective.

1.1 Strategic Human Resource Management

Employees can be considered an organization's most valuable assets (Boselie, 2014; Paauwe & Farndale, 2017). Reflecting this value, employees have been dubbed the *human resources* of organizations and their combined knowledge, skills, and abilities have been labelled the organizations' *human capital* (Baron & Armstrong, 2007; Coff, 2002). In order to compete and survive economically, organizations need to manage their human capital in a profitable and sustainable way (Barney, 2001; Baron & Armstrong, 2007; Huselid & Becker, 2011; Wright et al., 1994). This implies that organizations need to be effective and/or efficient in the way they hire, deploy, develop, motivate, and retain their employees. In academia, a whole stream of HRM research is dedicated to unveiling the optimal ways in which to organize and manage people in organizations. In practice, many contemporary organizations have a specialized HRM function – or (several) HRM professional(s) – in place to design and champion the policies and practices that should be implemented.

1.1.1 HRM & Performance

Since the eighties, the HRM function has sought to convince others of the ways in which it adds value to organizational operations (Boselie, 2014; Boselie, Dietz, & Boon, 2005; Boxal & Purcell, 2000; Paauwe, 2009; Paauwe & Farndale, 2017; Paauwe, Wright, & Guest, 2012). Mark Huselid (1995) was among the first to substantiate the claimed influence of HRM practices for organizational performance scientifically. His research demonstrated that the extent to which organizations implemented so-called *High Performance Work Systems* related to a reduction in employee turnover, improved organizational profits, and a higher market value (Huselid, 1995). Huselid's high performance systems included among others sophisticated selection and training practices, participation programs, formal performance appraisals, and contingent pay schemes. Since this seminal publication, a large body of research has demonstrated the impact of the HRM function and its policies and practices on the operational and financial performance of organizations (see Combs, Liu, Hall, & Ketchen, 2006; Crook, Todd, Combs, Woehr, & Ketchen, 2011; Jiang, Lepak, Hu, & Baer, 2012; Subramony, 2009). Currently, the leading paradigm is that HRM influences operational and financial outcomes because it improves employees' abilities, their motivation, and their opportunities to contribute to organizational goals (Jiang et al., 2012). Yet, not everybody is fully convinced of the positive impact of HRM. For example, there are three recurring topics of discussion: the causal order of effects, how to measure HRM impact, and the influence of context.

1.1.1.1 Causal Order

First, critiques have been raised regarding the causal direction of the relationship between HRM and performance. Early empirical studies exploring HRM's impact have used mostly cross-sectional or even post-predictive designs (Wright, Gardner, Moynihan, & Allen, 2005). Hence, their results do not provide conclusive evidence for the causal impact of HRM implementation. Recognizing this limitation, scholars have examined the effects of HRM via longitudinal research designs as well. Such longitudinal studies have generally found an equally positive impact of HRM on performance outcomes as the

results of the cross-sectional studies already indicated (Crook et al., 2011). However, they also demonstrated that the positive relationship between HRM and performance outcomes is often bidirectional (Guest, Michie, Conway, & Sheehan, 2003; Van de Voorde, Paauwe, & Van Veldhoven, 2010; Van de Voorde, Van Veldhoven, & Paauwe, 2010; Van Veldhoven, 2005). In this sense, more sophisticated HRM practices would not only lead to better performance but, the other way around, improved performance would also result in a higher degree of sophistication in HRM.

1.1.1.2 Balanced Perspective to Impact

Second, although improved organizational performance may be most interesting outcome to the organizational stakeholders implementing HRM, there are other relevant implications of HRM. Scholars have argued that a more *balanced perspective* is necessary to fully appreciate HRM's value (Paauwe, 2004). This balanced perspective would go beyond performance metrics and consider HRM's impact on outcomes relevant to employees, or even to society as a whole. This aligns with the notion that HRM should not be about exploiting employees as a means to an end (i.e., the *resource* part), but about stimulating the mutual exchange relationship between an employer and an employee (i.e., the *human* part). Interestingly, studies that employ a balanced perspective have demonstrated that mutual gains can be achieved to some extent. Investing in HRM relates to improvements in individual and organizational performance as well as improvements in employees' psychological well-being (Jiang et al., 2012; Kehoe & Wright, 2013; Van de Voorde, Paauwe, & Van Veldhoven, 2012). Only health benefits do not seem an immediate consequence of more sophisticated HRM implementation (Van de Voorde et al., 2012). When the general well-being of employees is also considered during HRM implementation, this could stimulate the organization's legitimacy and the attraction, motivation, productivity, and retention of employees, in turn, contributing to organizational performance in the long run (Boselie, 2014; Jiang et al., 2012; Paauwe & Farndale, 2017; Van de Voorde et al., 2012). In light of these mutual gains, implementing sophisticated and sustainable HRM practices seems in the best interest of organizations that seek long-term viability.

1.1.1.3 Importance of Context

A third, ongoing discussion regarding the impact of HRM is the role of context. Early HRM research had adopted a universalistic perspective where organizations that implement certain *best practices* in HRM will experience its positive impact (e.g., Huselid, 1995; Pfeffer, 1998). However, a different school of thought is that of the contingency or *best fit* perspective. Here, scholars argue that organizations should align their HRM policies and practices with their institutional, competitive, and cultural environment if they desire positive impact (Boxal & Purcell, 2011; Johns, 2006, 2017; Paauwe, 2004; Paauwe & Farndale, 2017; Ulrich & Dulebohn, 2015). This contingency perspective implies that the impact of HRM practices may vary between countries, sectors, and organizations. On top of this, research suggests that the impact of HRM may vary within an organization. On the one hand, employees differ in the ways in which they perceive and respond to HRM (Bowen & Ostroff, 2004; Croon, Van Veldhoven, & Peccei, 2014; Kehoe &

Wright, 2013; Nishii & Wright, 2007; Piening, Baluch, & Ridder, 2014; Snape & Redman, 2010). On the other hand, HRM initiatives may have more impact when implemented for certain employee categories. The impact would be greatest when HRM investments are focused on strategic job positions and the employees in these positions (Huselid & Becker, 2011). The performance of employees in such positions is relatively important for the performance of the overall organization, either through reduced cost or through increased revenue. Hence, any HRM investment in these jobs and employees will have a relatively high potential payoff. In practice, many contemporary organizations already differentiate their HRM investments; for instance, by distinguishing *talents* or *high potentials* within their employee populations (see Chapter 6). Overall, there is evidence for contextual influences on the impact of HRM, both between and within organizations.

1.1.2 Evidence-based HRM

What does the above scientific discourse imply for local HRM departments and the ways in which they manage the human capital of their employees? With a vast body of scientific literature on what constitutes effective HRM, it should be clear which HRM policies and practices should be implemented. Yet, faulty practices are abound in HRM as decisions are frequently based on personal preferences, unsystematic experiences, knee-jerking, fad chasing, and guesswork regarding what works (Rousseau, 2006; Rousseau & Barends, 2011).

Fortunately, there is increased interest in evidence-based decision-making in HRM. Evidence-based management involves *"translating principles based on best evidence into organizational practices*" (Rousseau, 2006, p. 256). According to Rousseau and Barends (2011), good evidence-based management combines four sources of information: (1) practitioner reflection and judgement, (2) stakeholders concerns, (3) scientific evidence, and (4) reliable and valid organizational metrics. The first two sources of information are nearly always present in the contemporary HRM function: HRM professionals are designing policies and practices in light of business, line management, and employee needs and the legislative context. The third source of information has become more important over the course of time. Currently, a strong basis of scientific evidence exists for what kind of HRM principles should work, built on the academic studies conducted in fields such as industrial, occupational, organizational, social and/or behavioral psychology, and general management and HRM research (Briner, 2000; Cascio & Aguinis, 2010; Charlier, Brown, & Rynes, 2011; Kaufman, 2010, 2014; Locke, 2009). The greatest deficit of the contemporary HRM function lies in the fourth source of information: HRM departments often lack the capability – both in skills and metrics – to measure and quantify the strategic contribution of their HRM activities, its bottom-line impact, and any progress therein in the own, local organizational context (Cascio & Boudreau, 2010; Paauwe & Farndale, 2017).

1.2 People Analytics

1.2.1 Need for People Analytics

The ability to measure and quantify the strategic impact of their activities in their own, local organization context would be very valuable for the HRM function. While scientific insights form a basis of evidence for many of the common HRM practices and thus provide some assurance for their effectiveness in general (e.g., performance appraisal, compensation; Briner, 2000; Cascio & Aguinis, 2010), this external evidence is by no means a guarantee for the esteemed impact of these HRM practices in local practice. To turn scientific research into practice, HRM practitioners first have to translate the scientific findings into a policy or a practice that would presumably render the same effect. Second, this policy or practice needs to be implemented, perceived, and responded to in ways in which the original effect is not lost (Nishii & Wright, 2007; Piening et al., 2014). Third, HRM research has shown that the context in which HRM is implemented is crucial to its effectiveness (e.g., Johns, 2006; Paauwe & Farndale, 2017), and what works for students in an academic lab may not necessarily work in an organizational context. Similarly, the effects of practices may differ between or within organizations (see Chapter 6; Johns, 2006; Huselid & Becker, 2011). All this implies that the effects of HRM, once implemented in practice, may thus vary considerably from what was found in the original scientific setting. Therefore, instead of blindly relying on scientific evidence, it would be valuable to double-check whether HRM activities actually achieve the esteemed effects in practice and to adjust where needed.

1.2.2 People Analytics Terminology

This process of internally examining the impact of HRM activities goes by many different labels. Contemporary popular labels include *people analytics* (e.g., Green, 2017; Kane, 2015), *HR analytics* (e.g., Lawler, Levenson, & Boudreau, 2004; Levenson, 2005; Rasmussen & Ulrich, 2015; Paauwe & Farndale, 2017), *workforce analytics* (e.g., Carlson & Kavanagh, 2018; Hota & Ghosh, 2013; Simón & Ferreiro, 2017), *talent analytics* (e.g., Bersin, 2012; Davenport, Harris, & Shapiro, 2010), and *human capital analytics* (e.g., Andersen, 2017; Minbaeva, 2017a, 2017b; Levenson & Fink, 2017; Schiemann, Seibert, & Blankenship, 2017). Other variations including *metrics* or *reporting* are also common (Falletta, 2014) but there is consensus that these differ from the analytics-labels (Cascio & Boudreau, 2010; Lawler, Levenson, & Boudreau, 2004). While HR metrics would refer to descriptive statistics on a *single* construct, analytics involves exploring and quantifying relationships between *multiple* constructs.

Yet, even within analytics, a large variety of labels is used interchangeably. For instance, the label people analytics is favored in most countries globally, except for mainland Europe and India where HR analytics is used most (Google Trends, 2018). While human capital analytics seems to refer to the exact same concept, it is used almost exclusively in scientific discourse. Some argue that the lack of clear terminology is because of the emerging nature of the field (Marler & Boudreau, 2017). Others argue that differences beyond semantics exist, for instance, in terms of the accountabilities the labels suggest, and the connotations they invoke (Van den Heuvel & Bondarouk, 2017). In

practice, HR, human capital, and people analytics are frequently used to refer to analytical projects covering the entire range of HRM themes whereas workforce and talent analytics are commonly used with more narrow scopes in mind: respectively (strategic) workforce planning initiatives and analytical projects in recruitment, selection, and development. Throughout this dissertation, I will stick to the label people analytics, as this is leading label globally, and in the US tech companies, and thus the most likely label to which I expect the general field to converge.

1.2.3 People Analytics Defined

What constitutes people analytics and how it differs from conventional scientific research on HRM is not well defined. People analytics has been defined as "*rigorously tracking HR investments and outcomes*" (Ulrich & Dulebohn, 2015, p. 202), as "*statistical techniques and experimental approaches […] to tease out the causal relationship between particular HR practices and […] performance metrics*" (Lawler et al., 2004, p. 4), and as "*data, metrics, statistics and scientific methods, with the help of technology, to gauge the impact of [human capital management] practices on business goals*" (Kryscynski, Reeves, Stice-Lusvardi, Ulrich, & Russell, 2017, p. 2). In reviewing people analytics literature, Marler and Boudreau (2017) synthesize multiple definitions and define people analytics as the "*HR practice enabled by information technology that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organizational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making*" (p. 15). Adding an HRM element to a general definition of analytics (Davenport & Harris, 2007, p. 7), people analytics can be defined as the *extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions involving personnel*. Arguably, this latter definition is more in line with a balanced approach than that of Marler and Boudreau (2017), which centralizes business impact specifically. Nevertheless, both definitions highlight the two related ways in which people analytics differs from a mere application of scientific rigor and methodology in practice. In comparison to conventional HRM research – a term I use here to refer to the traditional management and psychology research on HRM issues – people analytics often serves (1) a different purpose and may thus (2) follow a different statistical modelling process.

1.2.3.1 Different Purpose

First, people analytics differs from conventional HRM research because of its purpose. HRM research has primarily been concerned with uncovering, forming, and/or validating theory (Locke, 2007; Shmueli, 2010; Sutton & Staw, 1995; Van Aken, 2004; Yarkoni & Westfall, 2017). This approach is in line with Herbert Simon's (2001) definition of *basic science*, which seeks to describe the world and explain its observable phenomena to generate knowledge and understanding (p. 32). According to Woo, O'Boyle, and Spector (2017), "*the current zeitgeist of organizational science appears deeply vested in a 'top-down', deductive approach that relies primarily on testing a priori hypotheses*" (p. 255). Hence, in conventional HRM research, "*the role of theory is very strong*" and "*the reliance*

on data and statistical modeling are strictly through the lens of the theoretical model" (Shmueli, 2010, p. 290).

This explanatory focus is not without reason or consequences. Scientific publication procedures in management and psychology fields highly favor research with a deductive approach, where theory-driven hypotheses are tested in a confirmatory way (e.g., Hambrick, 2007; Leung, 2011; Pratt, 2008; Woo et al., 2017; Van Aken, 2004). There has been such "*a strong bias towards description-driven research, even to the extent that many feel that that is the only type of research that deserves academic respectability*" (Van Aken, 2004, p. 229). As a result, there has been a "*near-exclusive focus on developing mechanistic models of cognition that hold theoretical appeal but rarely display a meaningful capacity to predict future behavior*" (Yarkoni & Westfall, 2017, p. 1101). In conventional HRM research, *"management implications tend to be treated more or less as an afterthought of the analysis and are not tested as such"*, resulting in doubts about the actual relevance of contemporary research (Van Aken, 2004, p. 230).

People analytics serves a different purpose as highlighted in its definitions. People analytics is focused on uncovering practical insights or actions that are valuable in a specific organizational context. Here, data and statistical models are leveraged specifically to explain, predict, and/or prescribe how organizations can improve the impact of their HRM activities – be it on outcomes relevant to the business, to the employee, or to society as a whole. The insights (including predictions) generated by such research can be used directly as input for decision-making processes in local practice.

Such research focused on local, practical value is still considered *scientific*, and not necessarily new. In Herbert Simon's eyes, people analytics could be considered an *applied science*, seeking to make inferences or predictions in order to anticipate and adapt to the future and to invent and design practices (Simon, 2001, p. 32). Others would argue that people analytics as a *design science*, seeking to develop valid and reliable knowledge to be used in designing solutions to problems, thereby occupying the middle ground between descriptive theory and actual applications (Van Aken, 2004, p. 225). From the perspective of Gibbons and colleagues (1994), people analytics would be a form of mode 2 knowledge production: trans-disciplinary scientific research with intensive interaction between knowledge production, dissemination, and application. Furthermore, people analytics shows similarities to Action Research, collaborative (clinical) research, and case-study approaches (see Eden & Huckham, 1996; Rynes, Bartunek, & Daft, 2001; Van Aken, 2004). In sum, while people analytics seeks to generate knowledge and understanding about HRM phenomena like conventional HRM research does, its primary purpose is often more local and applied: to *predict* what works best in practice, in a specific context – now or in the future.

1.2.3.2 Different Statistical Modelling Process

Second, people analytics may follow a different statistical modeling process than conventional HRM research, among others due to its different purpose. Any statistical modelling process will consist of several general stages: study design, data collection, data preparation, variable selection, methods and algorithms, model validation, evaluation, and selection, and model usage and reporting. Each of these stages involves several

important decisions that have to be made, for instance, regarding construct operationalization, data handling, or modeling steps. These decisions will be led largely by the goal of the research and the type of modelling that is applied (e.g., descriptive, exploratory, explanatory, predictive; Shmueli, 2010; Woo et al., 2017). The stages of a conventional HRM research process – focused on building theory through explanatory modelling – will therefore frequently differ from those of a people analytics project – focused on organizational utility, regardless of the type of modelling.

These differences can occur in many ways. For instance, construct operationalization in conventional HRM research is largely determined through theoretical justification and prior scientific validation. If scholars want to measure *employee engagement*, they turn to previous literature to examine how they may measure each of its theoretical dimensions with a validated scale. In contrast, availability, organizational legacy, stakeholder requirements, and predictive and benchmarking utility will largely determine how constructs are operationalized in a people analytics project. On the one hand, these factors have affected how HRM phenomena have been measured in the past and thus what data may already be conveniently available (e.g., archival data on employee engagement by the definition of the organization under study). On the other hand, new people analytics initiatives will have to make concessions in order to gain organizational buy-in, thus affecting what and how data can be gathered in any future studies. Similarly, complex (e.g., high dimensional, high volume, high velocity), unstructured (e.g., image, sound, text), and/or dirty data (e.g., missing values, errors) are often valuable for people analytics projects but are less easily leveraged in conventional HRM research contexts, due to the data's unconventionality and its lack of theoretical foundation. Other potential differences between the statistical modelling processes of people analytics and conventional HRM research relate to the used methods, model evaluation processes, and model selection criteria (see Shmueli, 2010; Strohmeier & Piazza, 2013; Yarkoni & Westfall, 2017). In sum, the differences can be plentiful.

1.2.3.3 Potential Similarities

Important to note is that people analytics and HRM research are not necessarily different. People analytics merely seems to follow a more inductive approach, starting with the purpose in mind, and is thus more flexible in terms of the procedure to best fulfill this purpose (Woo et al., 2017). The modelling process can be matched to the HRM issue at hand rather than necessarily conforming to the conventional procedures. Still, any people analytics project can be very much similar to conventional HRM research. For instance, a people analytics project can consist of a replication of an earlier scientific study in the own organizational context, in order to inform decision-making. Alternatively, a people analytics project with the purpose of informing organizational decision-making could demonstrate value for the academic community and be published scientifically. Increasingly, scholars and practitioners are teaming up to conduct people analytics research that holds both academic and direct practical value (e.g., Harter, Schmidt, & Hayes, 2002; Kryscynski et al., 2017; Van de Voorde, Paauwe, & Van Veldhoven, 2010).

1.2.4 Public Interest in People Analytics

Regardless of the precise definition and demarcation, the rise in public interest in people analytics is quite remarkable. Figure 1.1 demonstrates the monthly Google search interest for several labels between 2004 and 2018. A locally weighted regression line (Cleveland & Devlin, 1988) was fitted to these monthly data to visualize the tremendous increase in interest in the domain since 2007. This interest in people analytics is due to at least three concurrent developments: (1) the rise of digital technology, (2) an increase in processing power, and (3) a push towards evidence-based HRM.

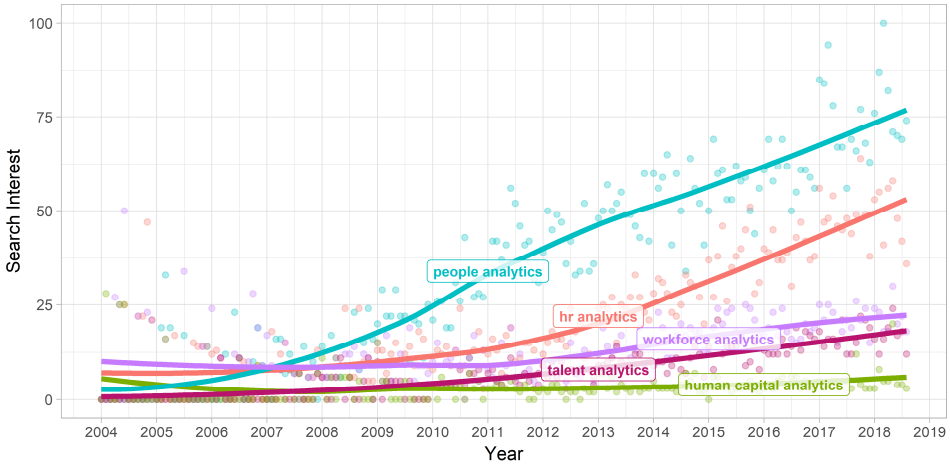

Figure 1.1: Monthly Google search interest on "people analytics" and related terms over time. Values are proportional to the maximum value and fit by locally weighted regression lines.

1.2.4.1 Digital Technology

First, digital technology – including personal computers, the Internet, and mobile devices – has changed and continues to change how we manage and organize work and the information we collect in the process. With the rise of digital HR information systems (HRIS), we have witnessed great increases in both the volume and the complexity of the data we gather on our personnel. Organizations used to keep physical records containing basic employee information locally whereas, nowadays, terabytes of workforce data can be gathered, processed, and monitored on a continuous basis in the cloud (Angrave, Charlwood, Kirkpatrick, Lawrence, & Stuart, 2016; Ball, 2010; Bersin, 2015; Deloitte, 2017; Günther, Mehrizi, Huysman, & Feldberg, 2017; Hendrickson, 2003; McAbee, Landis, & Burke, 2017). Concrete examples involve the gamification of work – where game features are added to a work context in order to provide real-time information on, for instance, employees' performance (Cardador, Northcraft, & Whicker, 2017) – or the collection and analysis of video data for HRM processes such as employee selection or safety management (Guo, Ding, Luo, & Jiang, 2016; Roth, Bobko, Van Iddekinge, & Thatcher, 2016). While the complex, novel data gathered via digital technology has the potential to improve our HRM decision-making, processing and analyzing such data often requires a different approach than the one we are used to in HRM research and practice

(see Chapters 2, 3, and 6; Angrave et al., 2016; McAbee et al., 2017; Shmueli, 2010; Yarkoni & Westfall, 2017).

1.2.4.2 Processing power

Second, it has become easier to analyze data and uncover (behavioral) patterns. Due to advances in computing power and developments in open-source programming languages (e.g., R, Python, Pig, Julia, Ruby) and libraries (e.g., caret, scikit-learn, Tensorflow, Theano), anyone with some statistical training can run complex analyses and large-scale simulations on their personal laptop. These days, *"given adequate data and access to a personal computer, a six-year-old could use a basic statistics program to generate regression results"*, Charles Wheelan jokingly states in his book *Naked Statistics* (2013, p. 187). On a larger scale, distributed databases and computing systems (e.g., Hadoop, Spark) allow organizations to scale their capabilities in order to handle, process, and analyze staggering amounts of data. Simultaneously, we see an improved dissemination of new methodology and a rise in interdisciplinary collaborations (see Chapter 2; James, Witten, Hastie & Tibshirani, 2013; Strohmeier & Piazza, 2013). As a result, models and techniques that are common in fields other than HRM (e.g., physical, life, computer, and medical sciences) are nowadays increasingly applied to solve personnel problems (see Chapters 3 and 6; Strohmeier & Piazza, 2013). These developments allow the HRM function to better leverage the value of its data.

1.2.4.3 Push towards evidence-based HRM

Third, the HRM function is experiencing a strong push to become more data-driven and evidence-based. The popular and the scientific press have shared success stories of progressive HRM departments (e.g., Bock, 2015; Rasmussen & Ulrich, 2015; Siegel, 2016) and of other functional disciplines (e.g., McAbee et al., 2017; McAfee, Brynjolfsson, Davenport, Patil, & Barton, 2012; Lewis, 2004), highlighting the enormous value that data analytics may bring. At the same time, the scientific community established that HRM affects operational and financial outcomes (e.g., Guest et al., 2003; Jiang et al., 2012), but that organizations may want to test the effectiveness of HRM policies and practices in their own, local context (e.g., Boselie et al., 2005; Johns, 2006; Lepak & Snell, 2002; Paauwe & Farndale, 2017). It seems that becoming more evidence-based and data-driven through analytics would provide the HRM function with huge benefits (Barends & Rousseau, 2011, p. 233). Data and analytics can allow organizations and their HRM departments to manage their personnel more effectively and/or efficiently, thus providing a competitive advantage. In practice, organizational stakeholders increasingly demand evidence of the impact of HRM decisions (Minbaeva, 2017a; Van der Togt & Rasmussen, 2017) and this causes HRM professionals to turn to people analytics to complement their intuition, experience, and beliefs with facts and evidence (Minbaeva, 2017a, p. 111).

1.3 Dissertation outline

This dissertation aims to answer two main research questions:

1. *What is the current state of people analytics?*

2. How can people analytics make HRM more evidence-based?

The first research question is approached from a wide perspective: to what extent have analytical initiatives been used to solve HRM issues and where do opportunities and hindrances for such people analytics lie? Hence, Chapter 2 sought to provide a first impression of the rise of data analytics in HRM and other functional domains, by looking at their respective streams of scientific research. Based on keywords provided by experts, I retrieved the networks of scientific publications that had examined analytics in light of organizational performance. Via network analysis and clustering techniques, I could subsequently estimate the extent to which data analytics has been applied to HR-related topics in order to improve the performance in and of organizations.

In Chapter 3, I pose that the pace of technological development may be one of the reasons behind the slow adoption rate of advanced analytics within both the practical and scientific HRM domains. In particular, the traditional HRM research methodology may be less suitable for the analysis of the novel HRM data collected via digital technology. Therefore, Chapter 3 demonstrates how HRM professionals and researchers could apply alternative methods in order to deal with these novel data structures. A more diversified methodological toolbox could help to distill value from the new forms of HRM data, with "new" and "old" approaches acting as complements.

The second research question is approached from a more narrow perspective – by focusing on a specific HRM issue. Aligning people analytics initiatives to strategic business issues facilitates the managerial buy-in for and progression of projects as their insights may inform concrete decisions and can thus have business impact. Therefore, Chapters 4 through 6 of this dissertation focus on the HRM topic of expatriate management.

Expatriate management is an interesting topic from a people analytics perspective for three main reasons. First, expatriation is strategically important to organizations. Multinational organizations can have thousands of employees on overseas, international assignments at any point in time. On the one hand, these assignments are crucial to their international business operations – for instance, to explore and establish new market opportunities or to manage the business operations abroad or offshore. On the other hand, these assignments are crucial to the establishment and development of a global talent pipeline – for instance, to attract and deploy talented employees on a global scale, or to provide (future) managers with valuable operational, international, cross-cultural, and cross-functional experiences.

Second, expatriation is quite costly to organize and manage. International assignment requires planning, preparation, administration, relocation, onboarding, premiums and allowances, and repatriation – often also for trailing family members. Expatriating talent is estimated to be up to four times more costly than hiring employees on local (non-expatriate) terms (McEvoy, 2011), with the total financial expenses of an international assignment ranging between $250k and $1M (Nowak & Linder, 2016).

Third, success or impact of expatriation is notoriously hard to quantify. In practice, it is unclear how and when the costly investment in expatriation pays off. Data, metrics, and analytics surrounding expatriation and its objectives are frequently underdeveloped. Similarly, scientific research on expatriation has been plagued by misconceptions and

shortsighted definitions surrounding expatriate success and failure (e.g., Harzing, 1995; Forster, 1997; Harzing, 2002). Hence, scholars and practitioners acknowledge the challenges in conceptualizing and measuring the return on investment of expatriation (Collings & Scullion, 2009; McNulty & Tharenou, 2004; McNulty, De Cieri, & Hutchings, 2009). Moreover, due to the nature of expatriation, scholars have to work with small samples. Here, a people analytics project can help to explore the impact of expatriation by combining practical insights, organizational data (volumes), and scientific rigor. Overall, expatriate management appears to be an interesting HRM topic to approach through the lens of people analytics, both from a scientific and from a practical perspective.

Chapters 4 and 5 explore the ways in which expatriate employees can be assisted on their costly, strategic international assignments. Such an exploration of previous scientific findings on a HRM topic, is often one of the early steps in any people analytics project. Chapter 4 was a first exploration on what constitutes successful international assignment and how organizational agents contribute to this process. Next, meta-analytical findings are often consulted in practice, in order to estimate what kind of effects one might expect. In Chapter 5, I apply meta-analytical techniques to synthesize the results of nearly a hundred scientific studies on expatriate success. Here, I aimed to establish a basis of evidence for the practices that organizations could focus their efforts on if they seek to influence certain outcomes of expatriation. Finally, Chapter 6 represents an operational application of people analytics within two large multinationals. I applied complex transformations and analysis to the HRIS data of over 9000 employees. This allowed a quantification of the strategic impact of three HRM practices on employee retention, taking into account the organizational context.

In conclusion, Chapters 2 and 3 of this dissertation elaborate on the past and future of analytical applications within the HRM domain whereas Chapters 4 and 5 focus on evidence-based insights for an applied HRM case: expatriate management. These two themes intersect in Chapter 6, where we use people analytics to quantify the impact of, among others, short-term expatriation. Throughout this dissertation, I underline the lagging development of – and barriers to – people analytics while also demonstrating how people analytics applications can provide valuable input for HRM decision-making. An overview of the chapters, their methodology, and the discussed research questions (RQs) is presented in Table 1.1.

Table 1.1: Dissertation outline

Chapter		Methodology	RQs
1	Introduction		1
2	The history, evolution, and future of big data and analytics: A bibliometric analysis of its relationship to performance in organizations	Network analysis	1
3	Expanding the methodological toolbox of HRM researchers: The added value of latent bathtub models and optimal matching analysis	Methodological paper	1
4	Expatriate support and success: A systematic review of organization-based sources of social support	Literature review	2
5	Fostering overseas success: A meta-analysis of the differential benefits of expatriate support	Meta-analysis	2
6	Paradoxes in international talent pipelines: HRM practices and the voluntary turnover of graduate recruits	Survival analysis	1, 2
7	Discussion		1, 2

2 The history, evolution, and future of big data and analytics: A bibliometric analysis of its relationship to performance in organizations

This chapter is submitted as Batistic, S. & Van der Laken, P. A. (n.d.). The history, evolution, and future of big data and analytics: A bibliometric analysis of its relationship to performance in organizations.

Big data and analytics are gaining momentum ever more quickly, particularly in the practitioner world. However, empirical evidence linking big data and analytics to improved performance in organizational contexts seems scarce and focused on the macro-level within specific management functions (mainly Information Technology). From Web of Science, we obtained a dataset of 327 primary studies and 1252 secondary papers in order to synthesize past research findings and advance our knowledge of applied big data and analytics. We explored the linkage between big data, analytics, and performance from a management perspective via three bibliometric review methods. First, we elucidate the intellectual foundations of the relationship via co-citation analysis. Second, we visualize the historical evolution of the field and its substreams via algorithmic historiography. Third, we provide insightful prospects on the field's potential evolution by means of bibliographic coupling analysis. Our results display the small dozens of somewhat dispersed streams of big data and analytics research as well as their fragmented evolution. However, our results also demonstrate that the move towards cross-functional collaborations has commenced. Finally, we provide insight into the state of data analytics in the different functional management domains and the gaps for both research and practice.

2.1 Introduction

Big data and analytics continue to spark interest among scholars and practitioners. Organizations are increasingly aware that they may transform and process their large data volumes to capture value for their businesses and employees (George, Haas, & Pentland, 2014). With the advent of more computational power, machine learning – particularly deep learning through neural networks – has become more broadly deployable in organizations. These techniques may realize the predictive value of big data, unleashing its strategic potential to transform business processes and providing the organizational capabilities to tackle key business challenges (Fosso Wamba et al., 2015).

When searched for the term "*big data*", the Web of Science Core Collection yields 3,347 hits in 2015, and over 4,000 publications in both 2016 and 2017. Some of these studies indeed demonstrate how big data and analytics (BDA) impact organizational performance, demonstrating that firms with data-driven strategies tend to be more productive and profitable than their competitors (Brynjiolfsson, Hill, & Kim, 2011; LaValle et al., 2011). Yet, very few attempts have been made to culminate this plethora of BDA research. Although some scholars have reviewed how organizational value can be derived from BDA, this relationship is often approached from a rather narrow information systems or information technology perspective (for some exceptions see Fosso Wamba et al., 2015; Grover & Kar, 2017; Günther, Rezazade Mehrizi, Huysman, & Feldberg, 2017). Calls to explore the impact of BDA from other organizational and management perspectives (e.g., human resources; Angrave et al., 2016) remain largely unanswered to this date.

A more comprehensive review of the implications of BDA for the management of performance in and of organizations seems warranted. Synthesizing past research findings is one of the most important tasks for advancing a field of research, particularly one characterized by an extensive growth of publications (Garfield, 2004; Zupic & Čater, 2015), such as BDA reserach. An overview of the BDA-performance debate may (a) delineate the subfields that constitute the intellectual foundation of the debate and how these subfields relate to one another, (b) unveil and explore the evolution and roots of the debate, and (c) provide insight into the future development of the debate. Moreover, by revealing discrepancies in the applications and perspectives within the different functional management domains and their research streams, a review may allow for cross-fertilization of best practices, research designs, and theoretical frameworks.

Particularly a bibliometric review, using science mapping would provide several advantages over classical qualitative and meta-analytical methods. First, a bibliometric approach is more macro-oriented because it allows the analysis of a comprehensive field of research. Researchers do not need to choose the exact relationship they wish to explore which offers increased objectivity in reviewing literature (Garfield, 1979). Second, science mapping consists of a classification and visualization of previous research (Small, 1999). This produces a spatial representation analogous to a geographic map that can demonstrate how knowledge domains and individual papers relate to one another. This seems particularly useful for BDA research because it spans between research domains (Günther et al., 2017) and may provide the "bigger" picture of the state of the art of these

domains combined. Science mapping may provide the bigger picture of the state of the art of these domains combined. Third, we use three different and complementary bibliometric methods. Via document co-citation analysis and algorithmic historiography, we explore respectively the past intellectual structure/foundations and the evolution of the BDA-performance debate whereas bibliographic coupling facilitates an objective exploration of the possible future state of research.

A bibliometric review of the relationship between BDA and organizational performance contributes to the literature in two ways. First, the bibliographic methods complement other qualitative and quantitative reviews. For instance, they allow a more comprehensive and objective exploration of the history and the evolution of the BDA – performance debate. Compared to previous reviews (see Günther et al., 2017 for some exceptions; Grover & Kar, 2017; Fosso Wamba et al., 2015), we are not limited to a specific focus, are able to include a larger sample of documents, and thus able to cover and discover more marginal topics within the debate. Second, the bibliometric approach may provide an objective speculation of the potential future of BDA research. Via bibliographic coupling, we hope to shift attention from traditions to future trends, proposing development areas for the future evolution of the debate. We aim to demonstrate how distant or disconnected topics may be linked through theory or empirical applications whereas emerging research fields may derive learning from those related and more established.

This paper will continue with a description of the sample, after which each of the three methods and their results will be discussed in separate sections. We conclude with an overall discussion, in light of previous reviews and the future trends resulting from our analyses.

2.2 General Methods

2.2.1 Sample

To identify the primary research papers on BDA and performance, we contacted 47 prominent scholars and practitioners who either published on BDA in general or on BDA in management fields (e.g., business studies, human resource management). These experts were asked to elicit ten keywords describing the relationship between BDA and performance at various levels (i.e., organizational, business unit, team, individual). Ten experts responded (21.3%), providing 90 keyword sentences which included 160 single keywords. The most frequently occurring keyword sentences were "*machine learning*" (n = 5), "*data science*" (3), "*analytics*" (2), "*deep learning*" (2), "*future*" (2), "*Hadoop*" (2), "*HR analytics*" (2), and "*sensors*" (2) whereas the single words "*data*" (13), "*learning*" (7), "*analytics*" (6), "*machine*" (5), and "*work*" (5) occurred most often. These keywords were used to build our comprehensive search strategy of 54 keyword combinations displayed in Table 2.1. Documents were thus included if they mentioned a BDA keyword as well as "performance" at a certain organizational level.

Table 2.1: Search keywords

BDA keywords AND	(Organizational level AND	Performance)
"machine learning"	organization	performance
"data science"	company	
analytics	firm	
"deep learning"	unit	
"big data"	team	
"artificial intelligence"	group	
	individual	
	employee	
	worker	

On September 7th, 2017, we searched the ISI Web of Knowledge bibliographic database, acknowledged as the most reliable database (Jacso, 2008; Bar-Ilan, 2008), for these keyword combinations and extracted the results of the relevant work-related domains (i.e., operation research, management science, business, business finance, psychology, psychology applied, management, sport sciences, and economics). This retrieved dataset included 324 primary documents which, in turn, provided 14,767 unique secondary (cited) documents.[1] In order to reduce the complexity of this latter dataset of secondary documents, we determined a citation threshold – the minimum number of citations a secondary document had to have to be included. Via an iterative approach (Zupic & Čater, 2015), a minimum threshold of two citations reduced our sample of secondary documents to 1252 papers. Table 2.2 demonstrates which journals published our primary and secondary papers.

2.2.2 Analyses

Three bibliometric analyses were conducted. Document co-citation analysis and algorithmic historiography were applied to the sample of secondary papers whereas bibliographic coupling was applied to the sample of primary papers. These three methods are explained in detail later.

Clusters of nodes in networks can be detected using modularity optimization. Detecting clusters in a network requires the partition of a network into communities of densely connected nodes. Here, one prefers the nodes belonging to different communities to be only sparsely connected. The quality of the partitioning can thus be quantified via the overall modularity of the network – a value that represents the density of links within communities as compared to links between communities. Hence, the best clustering solution is that in which the modularity is highest (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008; Newman, 2004). Because iterative clustering algorithms work with a random starting point, we exmined the robustness of our clustering solution. We ran Blondel and colleagues' clustering algorithm (2008) 50 times for each analysis (using Gephi's default resolution settings; i.e., 1.0) and calculated the average optimal number of clusters. Subquently, we chose the next solution where the number of clusters was equal to this average optimal number.

[1] Datasets available via https://bit.ly/2pHSb57

Table 2.2: The most frequent outlets for publications in the big data and performance debate

	Primary articles		Secondary (cited) articles	
	Journal	***N***	***Journal***	***N***
1	Expert Systems with Applications	61	MIS Quarterly	196
2	Decision Support Systems	27	Harvard Business Review	172
3	International Journal of Sports Science & Coaching	18	MIT Sloan Management Review	80
4	European Journal of Operational Research	14	Journal of Management Information Systems	49
5	International Journal of Production Research	8	Academy of Management Journal	44
6	Journal of Knowledge Management	8	California Managmenet Review	39
7	Journal of Business Research	6	Journal of Marketing	38
8	International Journal of Production Economics	6	Academy of Management Review	34
9	Frontiers in Human Neuroscience	6	Journal of the Association for Information Systems	31
10	Journal of Manageement Information Systems	6	Journal of Machine Learning Research	29

The cluster interpretation followed the suggestion of Zupic and Čater (2015). After running the cluster analyses (Study 1 and 3), the two authors independently explored the content of each cluster by reading through the abstracts and full text of the 25 publications with the highest weighted degree and recording any relevant keywords and topics. In a subsequent session, the authors compared and discussed their keywords, topics and interpretations, after which the current cluster names were determined.

2.2.3 Measures

Several network statistics were calculated during the analyses. The weighted degree centrality represents the number of edges (i.e., citation relationships) a node (i.e., document) has to other nodes, weighted for the edges' importance. Both incoming and outgoing edges are included in this measure. In general, the higher the weighted degree, the more important a document is to the network. Closeness centrality represents a node's distance to all other network nodes, inversed. The higher the closeness, the more central a document's location in the network. Finally, betweenness centrality represents a node's uniqueness in connecting other unconnected nodes. The higher the betweenness, the more a document functions as an important pathway connecting other documents (for more information see Nooy, Mrvar, & Batagelj, 2011).

2.3 Study 1: Document Co-citation

Co-citation analysis (McCain, 1990) uses the frequency with which two documents are cited together to determine their semantic similarity. The underlying assumption is that secondary papers which are co-cited (i.e., both referred to in the same primary document) share content-wise similarities and are thus semantically related. Co-citation count would thus indicate to what extent papers represent related key concepts, theories, or methods that a certain field or fields have or have drawn from (Small, 1973). Co-citation is a dynamic measure because it changes over time as documents accumulate

citations (Batistič, Černe, & Vogel, 2017). Therefore, it can reflect both the state of a certain intellectual field as well as the shifts in schools of thought (Pasadeos, Phelps, & Kim, 1998). Additionally, co-citations can reveal the intellectual roots of a scientific domain through the identification of its core, most cited works.

Via document co-citation analysis, we aimed to explore the historical overview of the big data – performance debate. The previously described database of secondary articles was normalized for association strength in VOSviewer (Van Eck & Waltman, 2014b), thereby acknowledging that certain nodes (secondary papers) are more important to the network because they have more connections. Subsequently, the normalized data was loaded into Gephi (Bastian, Heymann, & Jacomy, 2009) – the leading open-source visualization and exploration software for graphs and networks, which includes a broad statistics and metrics framework for network analysis, and allows flexibility in network refinement and visualization. Using a forced-directed network layout (Hu, 2005), we displayed nodes (i.e., papers) in a two-dimensional space in such a way that more related nodes are co-located whereas weakly related nodes are distant from each other.

2.3.1 Results

The 1252 documents in the co-citation network stabilized into ten clusters. The content of these clusters was assessed by examining the full texts of the most important articles by weighted degree. Consequently, the clusters were named (1) BDA Foundation, (2) Statistical Algorithms, (3) Marketing Analytics, (4) Customer Analytics, (5) Knowledge and Innovation, (6) Information Technology (IT) and Supply Chain (SC), (7) Adoption and Integration, (8) Corporate Social Responsibility, (9) Sports Analytics, and (10) Brain-Computer Interfaces (BCI). Table 2.3 provides an overview of these clusters and their articles.

The structure of the co-citation network (Figure 2.1) provided several insights. First, a large cluster of papers (N = 324), very central to the network, covers a variety topics that are seemingly the foundation for research linking BDA to performance in organizations. Popular publications explain how BDA and data-driven strategies provide organizations a competitive advantage (Barton & Court, 2012; Davenport, 2006; Davenport, Barth, & Bean, 2012; Davenport & Harris, 2007; Fosso Wamba et al., 2015; LaValle et al., 2011) whereas other publications focus on the impact of IT for organizational performance (Melville, Kraemer, & Gurbaxani, 2004; Devaraj & Kohli, 2003; Mithas, Ramasubbu, & Sambamurthy, 2011; Santhanam & Hartono, 2003; Tippins & Sohi, 2003). In either case, the resource-based view is theory that explains the impact (Barney, 1991; Bharadwaj, 2000). Others publications cover more methodological topics, such as structural equation modelling and partial least square (Fornell & Larcker, 1981; Hair, Ringle, & Sarstedt, 2011; Wetzels, Odekerken-Schröder, & Van Oppen, 2009), mediation (Baron & Kenny, 1986; Devaraj & Kohli, 2003; Tippins & Sohi, 2003), or measurement issues (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003; Santhanam & Hartono, 2003).

Second, this BDA foundation cluster is closely connected to several others clusters, which cover more specialized topics related to BDA. For instance, there is a separate

cluster focusing on how information technology and business intelligence and analytics add value to organizations (Elbashir, Collier, & Davern, 2008; Fairbank, Labianca, Steensma, & Metters, 2006; Kohli & Grover, 2008) particularly in improving supply chain management (Dehning, Richardson, & Zmud, 2007; Hendricks, Singhal, & Stratman, 2007; Kannan & Tan, 2005; Trkman, McCormack, de Oliveira, & Ladeira, 2010; Stadtler, 2005). Here too, the resource-based view seems a central theory (Newbert, 2007; Wade & Hulland, 2004). Another example is cluster five (N = 116), which we dubbed Knowledge and Innovation. It includes several seminal publications in the general BDA debate (e.g. Hsinchun, Chiang, & Storey, 2012; Manyika et al., 2011; McAfee & Brynjolfsson, 2012) – evidenced by their high weighted degree and closeness centrality in the network (Table 2.3) – but the majority of its publications is specifically focused on how organizations create, transfer, and manage knowledge, innovation, and learning (e.g., Cohen & Levinthal, 1990; Grant, 1996; Kogut & Zander, 1992; Nonaka & Takeuchi, 1995; Zander & Kogut, 1995). For more details, for instance, regarding the Marketing Analytics and Adoption and Integration clusters, we refer to Table 2.3 and the online appendix. [2]

Third, the cluster containing publications on statistics and machine learning algorithms was far removed from the above central clusters. Statistical innovations – such as the bagging of multiple predictors (Breiman, 1996) or decision tree and random forest algorithms (Breiman, 2001; Breiman, Friedman, Stone, & Olshen, 1984) – have only been fully leveraged by the customer analytics cluster (N = 124). Here, scholars have used advanced algorithms and predictive designs to try and predict customers' loyalty, retention and purchasing behaviors (e.g., Buckinx & Van den Poel, 2005; Larivière & Van den Poel, 2005; Verbeke, Martens, Mues, & Baesens, 2011). All the other large clusters seemed to draw on the algorithms cluster to a lesser extent.

For a fourth insight, we refer to the existence of cluster eight (N = 55) on the relationship between ethics, corporate social responsibility and firm performance. Most of its core publications (e.g., Berman, Wicks, Kotha, & Jones, 1999; Graves & Waddock, 1994; Russo & Fouts, 1997) show the (mutually) positive relationships between ethical and green business policies and their performance (for an exception, Hillman & Keim, 2001), as reverberated by the meta-analysis in this cluster (see Orlitzky, Schmidt, & Rynes, 2003). Other papers consider strengths and weaknesses of measuring corporate social responsibility with the social ratings of Kinder, Lydenberg, Domini Research & Analytics (e.g., Berman et al., 1999; Chatterji, Levine, & Toffel, 2009; Sharfman, 1996). Nevertheless, this CSR cluster remains somewhat dislocated from the main network.

Fifth and final, two small clusters were found: one on big data analytics in sport (N = 28) and one on brain-computer interfaces (N = 11). The publication dates of their main papers suggest that they are relatively emerging fields (see Table 2.3) and these clusters too appeared only marginally connected to the rest of the network.

Overall, Study 1 provided insights into the intellectual structure and foundation of the BDA-performance debate. The largest cluster included both the most renowned management literature on BDA as well as the scientific theories used to link BDA and

[2] Datasets available via https://bit.ly/2pHSb57

organizational performance. It seems closely knit with a cluster representing the IT and supply chain perspectives on BDA. The methodological/statistical cluster dealing with (big data) algorithms is situated in the periphery and attached to the network predominantly through Customer Analytics research (see Figure 2.1).

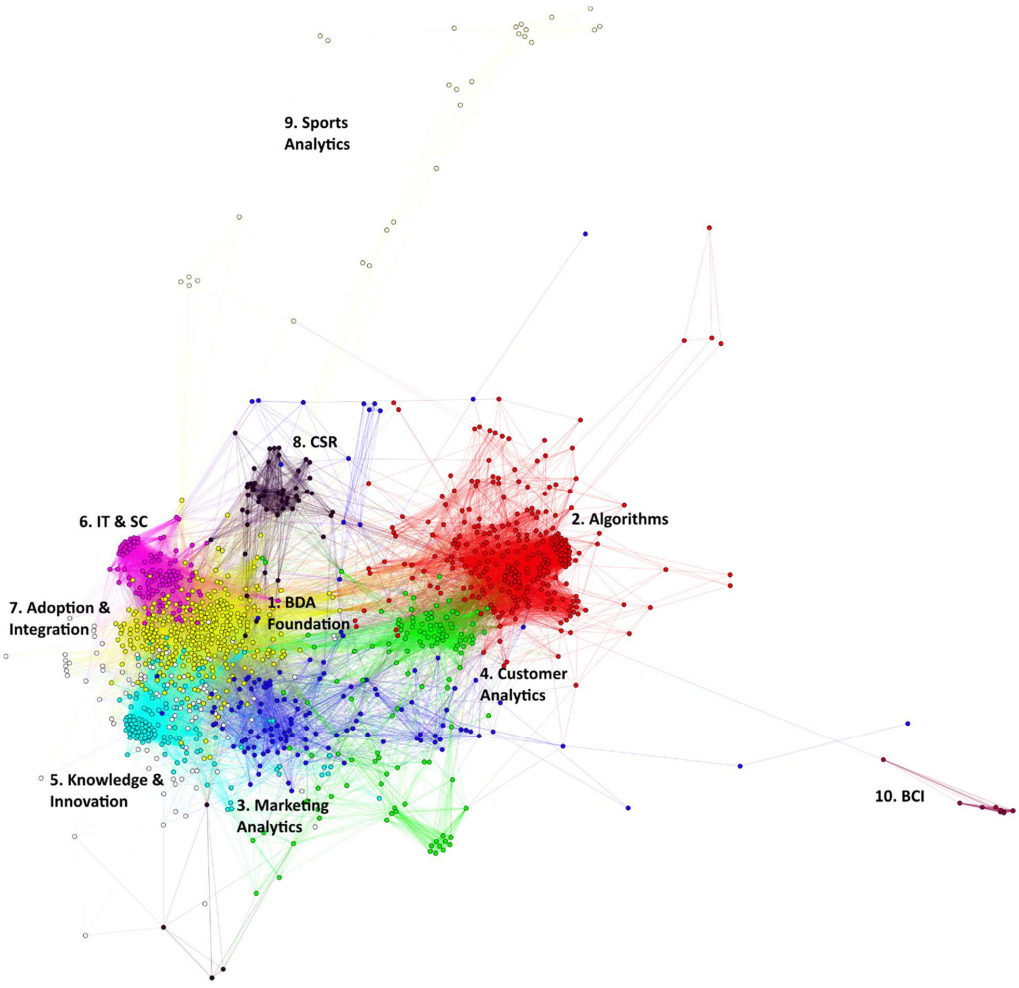

Figure 2.1: The co-citation network with 1252 secondary articles and ten clusters. Colours indicate the cluster to which a secondary paper has been assigned. Clusters represent closely related papers, which share thematic similarities.

Table 2.3: Statistics of the clusters and papers in the document co-citation network

Cluster (N)	Id	First Author, Year	Weighted Degree	Closeness	Betweenness
1. Big Data and Analytics Research Foundation (324)	67	Barney, 1991	582	.542	.058
	393	Fornell, 1981	548	.496	.012
	895	Podsakoff, 2003	493	.490	.015
	97	Bharadwaj, 2000	467	.484	.007
	985	Santhanam, 2003	455	.489	.007
2. Algorithms (264)	130	Breiman, 1996	371	.443	.020
	23	Altman, 1968	354	.464	.055
	132	Breiman, 1984	300	.450	.030
	1180	West, 2000	236	.398	.003
	131	Breiman, 2001	208	.428	.033
3. Marketing Analytics (131)	1170	Webster, 2005	87	.421	.001
	422	Germann, 2013	80	.414	.002
	1133	Vargo, 2004	72	.420	.001
	789	Michaelidou, 2011	70	.408	.001
	869	Pauwels, 2009	70	.406	.002
4. Customer Analytics (124)	492	Hanley, 1982	145	.422	.002
	305	Delong er, 1988	127	.422	.004
	664	Lariviere, 2005	121	.412	.001
	913	Prinzie, 2008	111	.416	.001
	1122	Van den Poel, 2005	111	.417	.001
5. Knowledge & Innovation (116)	743	Manyika, 2011	567	.538	.087
	188	Chen, 2012	550	.513	.042
	767	McAfee, 2012	482	.493	.025
	231	Cohen, 1990	457	.474	.016
	1179	Wernerfelt, 1984	415	.480	.016
6. Information Technology (IT) & Supply Chain (SC) (106)	633	Kohli, 2008	316	.465	.005
	1103	Trkman, 2010	314	.464	.009
	844	Nunnally, 1994	252	.450	.001
	1147	Wade, 2004	234	.448	.003
	412	Galbraith, 1974	218	.451	.004
7. Adoption & Integration (94)	182	Chatterjee, 2002	126	.426	.001
	480	Hambrick, 1984	126	.431	.007
	691	Liang, 2007	126	.426	.001
	262	Davenport, 1998	106	.444	.009
	572	Jansen jjp, 2005	104	.427	.000
8. Corporate Social Responsibility (CSR) (55)	1146	Waddock, 1997	109	.409	.003
	447	Graves, 1994	82	.383	.002
	858	Orlitzky, 2003	75	.399	.002
	1011	Sharfman, 1996	75	.368	.001
	961	Russo, 1997	73	.402	.002
9. Sports Analytics (28)	407	Gabbett, 2012	18	.246	.001
	409	Gabbett, 2014	18	.246	.001
	601	Kempton, 2013	18	.246	.001
	602	Kempton, 2015	18	.246	.001
	1035	Sirotic, 2011	18	.246	.001
1. Brain-Computer Interfaces (BCI) (11)	108	Blankertz, 2010	19	.232	.000
	375	Farwell, 1988	19	.232	.000
	477	Halder, 2011	19	.232	.000

Cluster (N)	Id	First Author, Year	Weighted Degree	Closeness	Betweenness
	481	Hammer, 2012	19	.232	.000
	625	Kleih, 2011	19	.232	.000

2.4 Study 2: Algorithmic Historiography

The development of a field over time can be displayed by ordering the most important publications in a field in the sequence in which they appeared, along with the citation relations between these publications (Garfield, 2004; Van Eck & Waltman, 2014a). Such an evolutionary visualization of a field illustrates the history of science and scholarship and has been referred to as an algorithmic historiography (Garfield, 2001; Garfield, 2004). Like other bibliometric methods, a historiography considers the relationships between various primary papers. However, the direction rather than the weight of this relationship is of importance as relationships are binary–a primary paper either does or does not cite a second primary paper. A historiography helps understanding paradigm shifts, as the changes in the citation of key papers of a field demonstrate how basic concepts and the overall perception of paradigms have changed over time (Garfield, Pudovkin, & Istomin, 2003).

We conducted the historiography in CitNetExplorer (Van Eck & Waltman, 2014a) on the earlier described full sample of secondary papers. CitNetExplorer is a software tool for visualizing and analysing citation networks of scientific publications. It is especially useful for analysing the development of a research field over time as it shows how publications build on each other. CitNetExplorer reduces this full citation network in two ways.

First, it identifies the "*core*" publications through the concept of k-cores (Seidman, 1983), where publications are considered core when they have a certain minimum number of ingoing or outgoing citation relations with other core publications. Van Eck & Waltman (2014a) consider publications core if they have citation relations with at least ten other core publications whereas Garfield and colleagues (2003) propose to limit the core publications to approximately 5% of the total number of publications. For our dataset, such settings resulted in a rather incomprehensive network with less than 21 publications. Therefore, we decided to expand this set iteratively - balancing the network's comprehensiveness and interpretability - which resulted in an optimal network of fifty core publications (approximately 15% of the total number of publications).

Second, CitNetExplorer performed a so-called transitive reduction of the citation network. Here, the program distinguishes essential from non-essential citation relations in the network, and only the essential relations are retained (Van Eck & Waltman, 2014a). Citation relations are classified as essential if there are no other pathways (i.e. relations) connecting two publications. Removing all non-essential relations minimizes the edges in the network while ensuring that all previously connected publications still have a pathway connecting them. Next, CitNetExplorer draws the nodes in the resulting network

by their publication year, on the vertical axis, and their closeness, on the horizontal axis (for a more details see Van Eck, Waltman, Dekker, & Van den Berg, 2010).

2.4.1 Results

The results of the historiography are presented in Figure 2.2, which clearly demonstrates that BDA-performance research has two main evolutionary streams. The first stream is rooted in statistics and algorithms and their application on financial and customer topics. The seminal paper by Altman (1968) is the root of this stream. After about forty years, several publications in Expert Systems with Applications followed, examining the application of predictive analytics within finance, such a credit risk scoring (e.g., Twala, 2010; Wang, Hao, Ma, & Jiang, 2011). The first stream includes several other root papers with a more statistical orientation (e.g., classification and regression trees, bagging, random forests) (Breiman, 1996, 2001; Breiman et al., 1984). The contemporary papers that arise from this root also cover predictive analytics, but focus on predictions regarding customer behavior (e.g., Ballings & Poel, 2012). Generally speaking, the left side of Figure 2 relates to the development of new statistical methods and applications within the fields of financial and customer analytics.

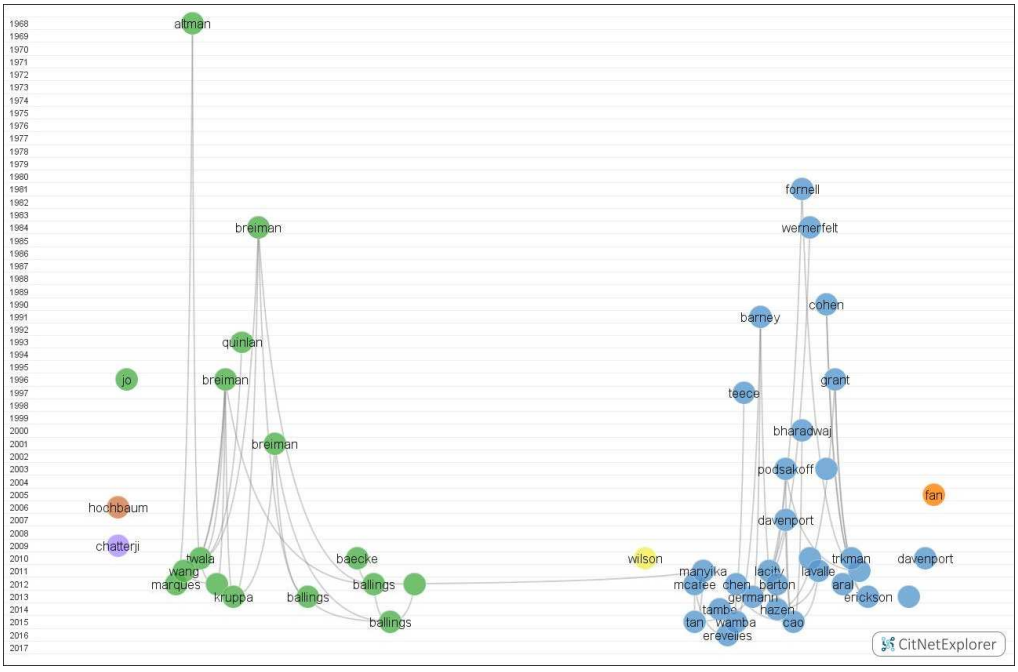

Figure 2.2: Citation network of the evolution of the big data – performance data. Curved lines indicate citation relations. Colours represent the cluster to which primary papers have been assigned. Clusters represent closely related papers, sharing thematic similarities.

Second, a more management and strategically oriented stream evolved on the right side of Figure 2.2. Although the first paper has focuses on methodology, structural equation modelling in specific (Fornell & Larcker, 1981), other root papers in this second

stream discussed the resource-based view (Barney, 1991), the dynamic capabilities of organizations (Wernerfelt, 1984), and a knowledge-based theory of organizations (Barney, 1991; Grant, 1996; Wernerfelt, 1984). This foundation has resulted in two main themes in contemporary papers within the stream. On the one hand, there is a general discussion regarding how big data and analytics affect organizational performance and specifically the performance of several business functions (e.g., supply chain, human resource management) (LaValle et al., 2011; Trkman et al., 2010). On the other hand, there are papers discussing the general topics of business intelligence and analytics in this second stream (Fosso Wamba et al., 2015; Hsinchun et al., 2012). These publications mostly explored the theory behind and evidence for impact of business intelligence, analytics and big data on organizational performance, but lack rigorous advanced analytical methods.

An interesting final deduction we can make from Figure 2.2 is that the above two evolutionary streams have only recently been connected. The responsible papers cover customer event history (Ballings & Poel, 2012) and the ways in which BDA may form a competitive advantage for organizations (Manyika et al., 2011).

Overall, where Study 1 elucidated the intellectual foundation and structure of the field, Study 2 added to this by providing an overview of its historical evolution. Some findings of the two studies overlap. For instance, the large gap between the methodological and theoretical discussions surrounding BDA is visible in both Figures 2.1 and 2.2. Moreover, the paper linking the two evolutionary streams in Figure 2.2 studied customer event history (Ballings & Poel, 2012) whereas the Customer Analytics cluster bridged the algorithms with the rest of the network in Study 1.

2.5 Study 3: Bibliographic Coupling

Bibliographic coupling examines the extent to which documents cite the same secondary documents. This implies that the primary, citing document is the focus of analysis rather than the cited, secondary documents (Vogel & Güttel, 2013). The general assumption is that the more the bibliographies of two documents overlap, the stronger their connection is.

Bibliographic coupling is different from other bibliometric methods as it does not derive the importance of papers within a scholarly community from their citation count or relations (Verbeek, Debackere, Luwel, & Zimmermann, 2002). This prevents an (over)emphasis on mainstream documents that may be popular but insignificant to a fields' intellectual development. Moreover, because it relies on the references within documents, the results of bibliographic coupling are more stable over time because reference lists do not change over time (in contrast to citation counts and relations). All this makes coupling particularly suitable for detecting current trends and future priorities as these are commonly covered in the more recent publications, which inherently are not the most cited.

Although we intended to use the retrieved dataset of 324 primary papers in the bibliographic coupling, only 211 of these primary documents (65.12%) were interconnected in the same network. The other papers had completely unconnected reference lists and were thus automatically removed by VOSviewer (Van Eck & Waltman,

2014b). The normalized network data of the included papers was loaded into Gephi (Bastian et al., 2009), and visualized with a forced-directed layout (Hu, 2005).

2.5.1 Results

The 211 primary documents in the bibliographic coupling network formed eight clusters. Table 2.4 provides an overview of the clusters and the most important articles (by weighted degree) per cluster. Based on the full text of their most important articles, we named the clusters (1) Risk and Customer Predictions, (2) Strategic BDA, (3) Information and Knowledge Management, (4) Text and Genetic Algorithms, (5) CSR, (6) Clustering, (7) Sports Analytics, (8) BCI.

Three large clusters arose in the network. The largest cluster (N = 74) includes several papers predicting the financial risk of credit applicants (Abellán & Castellano, 2017; Florez-Lopez & Ramon-Jeronimo, 2015; Twala, 2010; Wang et al., 2011), the likelihood of customers leaving or staying (i.e., customer churn; Ballings & Poel, 2012; Moeyersoms & Martens, 2015; Morales & Wang, 2010), and more niche prediction topics, such as social media usage (Ballings & Van den Poel, 2015). Papers in the second cluster (N = 56) examined what organizational characteristics affect firm performance in the era of BDA (Akter et al., 2016; Ji-fan Ren et al., 2017; Wamba et al., 2017) and how BDA improved decision-making and value creation in organizations (Cao, Duan, & Li, 2015; Chae, Olson, & Sheu, 2014; Chae, Yang, Olson, & Sheu, 2014; Chen, Preston, & Swink, 2015; Coltman, Devinney, & Midgley, 2011). A closely connected third cluster (N = 40) focused on how knowledge and information can be strategically developed, managed and leveraged in organizations (e.g., Erickson & Rothberg, 2013), and the role of BDA therein (Rothberg & Erickson, 2017; Tsui et al., 2014; Wang et al., 2013).

Five smaller clusters were also identified. Cluster four (N = 19) examined how text analytics and sentiment analysis of social media data can, for instance, predict stock markets (Kim & Kim, 2014; Nguyen, Shirai, & Velcin, 2015; Van de Kauter, Breesch, & Hoste, 2015), criminal activities (Gerber, 2014), or optimal product design and marketing strategies (Lau, Li, & Liao, 2014). Other papers in this fourth cluster explore genetic algorithms in relation to stock markets predictions (Esfahanipour & Mousavi, 2011) and production line optimization (Balakrishnan, Gupta, & Jacob, 2006). Cluster five (N = 10) examined corporate social responsibility research that used the ratings of Kinder, Lyndenberg, Domini Research and Analytics (e.g., Lucas & Noordewier, 2016; Nandy & Lodh, 2012). Cluster six (N = 6) examined how clusters can be identified and ranked in order to improve recommendation engines and other business processes (e.g., Chen, Cheng, & Hsu, 2013; Song, Yang, Siadat, & Pechenizkiy, 2013). Studies in cluster seven used BDA in sports to analyse the evolution of gameplay in Australian football (Woods, Robertson, & Collier, 2017), the relationship between practice and injury in American football (Wilkerson et al., 2016), and the possession value (Kempton, Kennedy, & Coutts, 2016) and match demands in rugby football (Hogarth, Burkett, & McKean, 2016). Finally, the two studies in cluster eight used machine learning to predict the performance of brain-computer interfaces (Halder et al., 2013; Hammer et al., 2014).

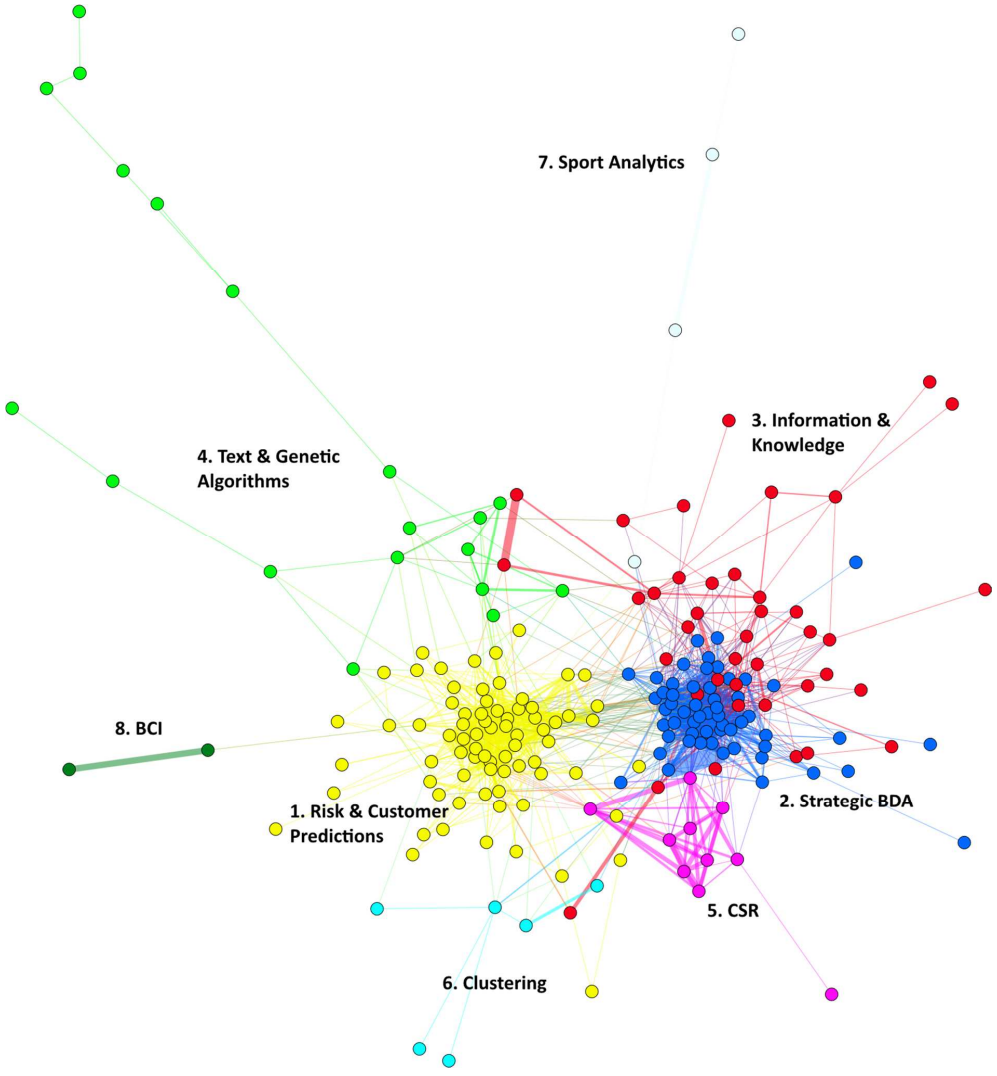

Figure 2.3: The bibliographic coupling network with 211 articles and 8 clusters. Line strength reflects bibliometric overlap. Colours represent the cluster to which primary papers have been assigned. Clusters represent closely related papers, sharing thematic similarities.

Table 2.4: Statistics of the clusters and papers in the bibliographic coupling network

Cluster (N)	Id	First Author, Year	Weighted Degree	Closeness	Betweenness
1. Risk & Customer Predictions (74)	165	Twala, 2010	150	.420	.020
	62	Florez-Lopez, 2015	141	.461	.031
	175	Twala, 2009	139	.417	.017
	64	Ballings, 2015	96	.431	.026
	129	Ballings, 2012	94	.448	.032
2. Strategic Big Data and Analytics (56)	13	Ren, 2017	201	.441	.008
	102	Chae, 2014	193	.451	.018
	23	Wamba, 2017	177	.470	.044
	24	Akter, 2016	170	.477	.060
	149	Coltman, 2011	147	.417	.013
3. Knowledge & Information (40)	15	Rothberg, 2017	118	.454	.032
	111	Erickson, 2013	64	.385	.006
	57	Jarvinen, 2015	41	.387	.012
	191	Cross, 2006	40	.391	.023
	205	Osborn, 1998	29	.385	.010
4. Text & Genetic Algorithms (19)	65	Van de Kauter, 2015	17	.359	.016
	88	Lau, 2014	14	.385	.038
	52	Nguyen, 2015	9	.319	.001
	85	Kim, 2014	9	.297	.001
	150	Esfahanipour, 2011	8	.297	.007
5. Corporate Social Responsibility (CSR) (10)	35	Lucas, 2016	55	.400	.014
	130	Nandy, 2012	46	.384	.027
	124	Boesso, 2013	45	.324	.001
	178	Chatterji, 2009	43	.320	.000
	60	Kang, 2015	41	.341	.002
6. Clustering (6)	116	Song, 2013	9	.340	.022
	107	Chen, 2013	8	.307	.001
	193	Hochbaum, 2006	7	.327	.001
	71	Ghazarian, 2015	2	.286	.000
	75	Munivrana, 2015	1	.254	.000
7. Sport Analytics (4)	33	Hogarth, 2016	7	.207	.010
	48	Kempton, 2016	7	.261	.019
	12	Woods, 2017	5	.349	.028
	31	Wilkerson, 2016	1	.172	.000
8. Brain-Computer Interfaces (BCI) (2)	121	Halder, 2013	11	.265	.010
	89	Hammer, 2014	10	.210	.000

While Study 1 and 2 looked at the historic structure and evolution of the BDA-performance debate, the purpose of Study 3 was to look ahead, at the future of the debate. Again, predictive analytics and customers are central to the network displayed in Figure 3.3, similar to the findings displayed in Figures 2.1 and 2.2. Similar to the co-citation analysis (Figure 2.1), clusters relating to new technological and methodological advances (e.g., brain-computer interfaces, text analysis, genetic algorithms) seem to arise at the periphery of Figure 3.3. In terms of important publications in the future of the debate, Study 3 puts forward Ji-Fan Ren et al. (2017) and Wamba et al. (2017), both in the Strategic BDA cluster and published in International Journal of Production Research and

Journal of Business Research respectively. Both these studies examined the effect of BDA on organizational performance in light of dynamic organizational capabilities.

2.6 Discussion

This paper reviewed literature on the relationship between big data, analytics and the performance in and of organizations. Three bibliometric method (co-citation analysis, algorithmic historiography, and bibliographic coupling) were applied to a dataset of 324 primary papers and 1252 secondary, cited papers collection via the ISI Web of Knowledge Database. VOSviewer, CitNetExplorer, and Gephi were used to process and visualize the bibliometric networks. The results provided insight into the intellectual foundation and structure, the historic evolution, and the future evolution of research on BDA and organizational performance. Most saliently, clusters of research on predictive analytics were found related to financial risk management, customer relationship management, and, to some extent, marketing. Research using BDA within the functional management domains of supply chain and information technology was also identified but discourse here focused on business intelligence and relationships at an organizational level. Other functional management domains, such as human resource management or legal, seem to be trailing behind, at least in terms of scientific output. The following section discusses the findings in more detail, comparing them to prior review findings, discussing some of our limitations and providing suggestions for future research.

2.6.1 Main Findings & Theoretical Contribution

Our bibliometric review is among the first to provide a comprehensive overview of the different perspectives that have been used to explore the implications and applications of BDA for organizational performance at various levels. Here, we discuss the four main insights.

First, we found significant overlap and several gaps when comparing our results to those of earlier reviews. Similar to earlier work, we found that BDA is already implemented in the management of customers, information, innovation, technology, and supply chain (Fosso Wamba et al., 2015; Grover & Kar, 2017), and that key topics include machine learning, business intelligence, text analytics and social media data (Grover & Kar, 2017). Moreover, our results cover four out of the six BDA debates found by Günther et al. (2017): our clusters deal with algorithms, the organizational capabilities BDA provide, BDA innovation and strategies, and corporate social responsibility. The inductive-deductive debate and the modes of big data access were not covered in our review. While the number of scientific publication in our reviewed sample was considerably larger than prior reviews, our focus was narrower (i.e. performance in organizations). Potentially, as a result, our review did not replicate the big data research streams in healthcare, education, and public management/government (Grover & Kar, 2017; Fosso Wamba et al., 2015; Sheng et al., 2017).

Second, our review provided several new insights. For example, all three analyses display that there are, at best, weak linkages between the strategic management of organizations in the era of BDA, and the actual implementation and operationalization of

BDA. The co-citation network (Figure 2.1) – exploring the intellectual roots of the BDA-performance debate – demonstrated a strong divide between the core BDA research stream and the clusters developing and implementing predictive algorithms. Similarly, the historiography (Figure 2.2) – exploring the historical evolution – and the bibliograhic coupling (Figure 2.3) – exploring the future evolution and trends – illustrated the weak overlap in the shared knowledge and discourse between the research streams covering strategical issues in BDA research (e.g., value, management, ethics) and those covering operational implementations (e.g., algorithms, applied analytics, predictive analytics, text analytics, clustering). Relatedly, it is worth to note that over a third of the primary documents could not even be included in the bibliographic coupling analysis because they lacked bibliographic connections to any other document in the network. This is a worrying development, considering that a vast amount of information and knowledge – including potential best practices or novel algorithms – is not diffused in the greater scientific community. Fortunately, this seems to be improving. Our historiography (Figure 2.2) demonstrated that the first bridges between these two research streams have recently been established by Ballings and Poel (2012) and Manyika et al. (2011).

Third, our studies suggest that the various management functions in organizations are in different stages of BDA maturity. In particular, the use of BDA seems established in relation to financial management and customer management and development, where big data and the more advanced statistical algorithms are already widely researched, discussed, and applied. Figures 2.1 and 2.3 suggested that developments within marketing, supply chain, and IT are on their way as well. However, research in these functional domains is focused mostly on the high-level, strategic impact of BDA (Chen et al., 2015; Germann, Lilien, & Rangaswamy, 2013; Trainor, Andzulis, Rapp, & Agnihotri, 2014; Trkman et al., 2010) rather than actual applications or individual-level predictions within these areas (for some exceptions see Ballings, Van den Poel, Hespeels, & Gryp, 2015; Chi, Ersoy, Moskowitz, & Ward, 2007; Esfahanipour & Mousavi, 2011). The other management functions seem to be trailing behind. For instance, although studies mention the rise of BDA and algorithmic intelligence in the HR domain (e.g., LaValle et al., 2011), little focused academic research has been conducted in this space. Arguably, this is undesirable: HR missing the big data bandwagon may imply a loss for organizations and cause harm for employees, whose interests would consequently be overlooked in BDA initiatives (Angrave et al., 2016). Similarly, we did not encounter studies on the use of BDA in the public sector or in relation to legal, procurement, M&A, health and safety, or facility management, leaving potential impact for predictive analytics and data-driven strategies in these areas (cf. Reinmoeller & Ansari, 2016; Sheng et al., 2017).

A third insight relates to the cluster on the corporate social responsibility that arose in both the co-citation and bibliographic coupling networks. Although the core publications in these clusters did consider the effect of (perceived) corporate social responsibility on organizational performance, they may have had little to do with BDA (e.g., Chatterji et al., 2009; Lucas & Noordewier, 2016; Waddock & Graves, 1997). On the one hand, due to the proprietary nature of social and environmental ratings such as those of Kinder, Lyndenberg, Domini Research and Analytics (currently MSCI), we cannot

accurately assess whether these data are truly "big" or "smart", or how analytics is involved in the process. On the other hand, the studies in these CSR clusters did not employ the more advanced, predictive algorithms but rather relied on traditional linear and logistic regression methods. We had hoped to find studies demonstrating how organizations may deal with ethics and privacy concerns when deriving business value through BDA, or how organizations may use BDA to solve costly environmental issues, such as pollution or energy waste. In our eyes, both of these themes would be interesting avenues for future research connecting BDA, CSR, and performance.

2.6.2 Limitations

This study faces several limitations, of which we discuss three below. A first limitation involves our search strategy. Although we reached out to nearly fifty experts in the field, only ten responded with keywords for our search. Their responses were internally consistent and had high face validity (e.g., *big data, machine learning, deep learning, data science, analytics, artificial intelligence*), but may have had a strong influence on our results. For instance, one could question whether the more distant clusters (e.g., brain-computer interfaces) belong in a review on BDA and performance in organizations. Alternatively, our search strategy may have caused an underrepresentation of specific data types (e.g., wearables, sensors), algorithms (e.g., long-short-term memory networks), or sectors (e.g., healthcare, governments).

Second, the interpretation of the results – the networks and the clusters – was limited to our human capabilities in terms of text and information processing. In line with the topic of big data and analytics, future studies could extend our current analysis with a more data-driven approach. For instance, text mining algorithms such as latent Dirichlet allocation (Blei, Ng, & Jordan, 2003) could be used to identify the state of the art topics in big data research. Unfortunately, we were unable to perform such analysis due to the nature of the data extracted from VOSViewer.

A third and final limitation is that we had to apply certain thresholds in order to process the data. Here, we followed the established guidelines (i.e., Eck & Waltman, 2014a; Garfield et al., 2003) and we compared different settings in order to test the robustness of analyses. Nevertheless, we acknowledge that these thresholds may have introduced bias in the otherwise relatively objective bibliometric methods.

2.6.3 Future Research Directions

Despite these limitations, the current review extends our knowledge of how BDA influences the management and performance of organizations. Based on the results, we have two main directions for future research, related to cross-functional collaborations and to ethics.

First, we demonstrated that the cross-functional adoption and application of BDA is scarce, but imminent. While scholars have noted that management researchers within certain streams are too strongly reliant on traditional methodology (e.g., general linear models) and therefore unable to realize the full potential of the "big" data collected through novel technologies (e.g., social media, wearables, sensors, video, audio) (Angrave et al., 2016; Chapter 3), the first bridges have been made. Future scholars and

practitioners should jump on the bandwagon and seek cross-functional collaborations, where domain experts within managerial functions team up with experts in statistics and machine learning in order to test their academic theories and deploy relevant business solutions. Preliminary empirical evidence from fields such as operation management and IT shows that collaborations between functional management domains and statistical researchers can add great value to organizational performance (cf. Wamba et al., 2017).

One such direction would be to apply advanced statistical methods to leverage value from big data in business functions that are yet underexposed. For instance, in HR, BDA could be used to predict the hiring success of applications, the effectiveness of training courses, or the number of workplaces needed. Another interesting knowledge-sharing opportunity lies in peripheral clusters, such as Sports Analytics where novel measurement methods (e.g., wearables, sensors) are already being used to optimize a variety of processes. Dissemination of such knowledge to more mainstream clusters of management research could be benecial for future operations in organizations. For example, wearables can be used to explore the communication patterns in organizations with the aim of improving knowledge sharing, or to monitor employees' health in order to improve their well-being (e.g., Wenzel & Van Quaquebeke, 2017).

Second, ethical considerations are essential in BDA research (Boyd & Crawford, 2012; Herschel & Miori, 2017). It goes without saying that all researchers should make sure that the privacy and the interests of their study subjects are protected, but ethicality is even more important when dealing with "big" data types such as continuous audiovisual, biometric, behavioral, or geolocation monitoring. Particularly when it comes to predictive analytics, scholars and practitioners should take additional care in preventing the creation of self-fulfilling prophecies or the incorporation of human bias into decision-making algorithms (Herschel & Miori, 2017). Additionally, big data and analytics are often seen as objective and accurate (Boyd & Crawford, 2012) whereas this is not necessarily the case. Nevertheless, complex and inaccurate data or predictions can create a false sense of authority that, as a result, becomes undisputable in organizations.

In light of these precautionary notes, we were surprised that our results did not include clusters or core papers specifically exploring the ethical perspectives related to BDA or the ethical issues related to predictive analytics. We call for future research examining to what extent the above issues occur in organizations, how they are currently handled, and what best practices can be implemented from a management perspective to prevent them. In practice, continuously exploring and testing both the financial and ethical implications of their analytical initiatives would allow organizations to establish their long-term survival firmly.

3 Expanding the methodological toolbox of HRM researchers: The added value of latent bathtub models and optimal matching analysis

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Researchers frequently rely on general linear models (GLM) to investigate the impact of human resource management (HRM) decisions. However, the structure of organizations and recent technological advancements in the measurement of HRM processes cause contemporary HRM data to be hierarchical and/or longitudinal. At the same time, the growing interest in effects at different levels of analysis and over prolonged periods of time further drives the need for HRM researchers to differentiate from traditional methodology. While multi-level techniques have become more common, this paper proposes two additional methods which may complement the current methodological toolbox of HRM researchers. Latent bathtub models can accurately describe the multi-level mechanisms occurring in organizations, even if the outcome resides at the higher level of analysis. Optimal matching analysis can be useful to unveil longitudinal patterns in HRM data, particularly in contexts where HRM processes are measured on a continuous basis. Illustrating the methods' applicability to research on employee engagement, this paper demonstrates that the HRM community – both research and practice – can benefit from a more diversified methodological toolbox, drawing on techniques from in- and outside the direct field to improve the decision-making process.

3.1 Introduction

Human resource management (HRM) emerged as a function in the early 20th century to effectively manage and rationalize the employment relationship (Ulrich & Dulebohn, 2015). Nowadays, HRM is increasingly becoming a 'science' that aims to enhance the decisions organizations make regarding their human capital (Boudreau & Ramstad, 2005; 2007; Rasmussen & Ulrich, 2015; Ulrich & Dulebohn, 2015). In creating a basis of evidence for such decisions, HRM scholars have primarily relied on general linear models (GLM) such as linear regression. However, the data gathered and compiled in the contemporary HRM function is increasingly of hierarchical and longitudinal nature, causing the current methodological toolbox of HRM researchers to fall short (Angrave et al., 2016; Bersin, 2015).

Methods other than GLM may better account for the complex effects in these new forms of HRM data. On the one hand, organizational entities are hierarchical structures which causes the effects of HRM to occur at and across different levels of analysis simultaneously (Hitt, Beamish, Jackson, & Mathieu, 2007; Wright & Nishii, 2007). On the other hand, as measurement happens on a more continuous basis, HRM data structures often consist of many observations nested within subjects over prolonged periods of time (Angrave et al., 2016; Bersin, 2015). Acknowledging the above, scholars have been increasingly moving from GLM applied at a single level of analysis towards multi-level techniques (Boselie, Dietz, & Boon, 2005; Sanders, Cogin, & Bainbridge, 2014; Snape & Redman, 2010). However, the most commonly applied multi-level methods do not work well when examining bottom-up effects, linking individual phenomena to organizational-level outcomes, and they can become overly complex when examining multiple, potentially categorical, variables simultaneously and over prolonged periods of time.

This article proposes two statistical methods that are rarely applied to HRM research questions, despite having added value over and above more traditional methodology. First, bathtub models are proposed as a way to account for multi-level models where the outcome resides at the higher level of analysis. Outperforming traditional aggregation and disaggregation approaches (Bennink, 2014), bathtub modeling can add value to HRM research on, among others, group composition or bottom-up effects. Second, optimal matching analysis (OMA) is advocated for its ability to detect longitudinal patterns. It can reduce large volumes of both categorical and ordinal data into a smaller set of underlying trajectories. Although relatively unknown in the general HRM field, it has been a valuable tool for career pattern analysis (Dlouhy & Biemann, 2015). This paper aims to demonstrate the added value of each method to the HRM methodological toolbox by discussing their applicability to research on employee engagement. After discussing each method's strengths and weaknesses separately, the paper concludes with overview of potential future applications and synergies.

3.2 Bathtub Modeling and Engagement

Over the past two decades, the influence of HRM on organizational performance has received much scholarly attention (e.g., Becker & Gerhart, 1996; Paauwe, Guest, & Wright, 2013) and a major part of the impact of HRM policies and practices has been demonstrated to be indirect via the behavior of employees (Christian, Garza, & Slaughter,

2011; Harter, Schmidt, & Hayes, 2002; Jiang, Lepak, & Baer, 2012; Kehoe & Wright, 2013; Subramony, 2009). However, an investigation of this mediational process is complex as it involves measurements at various levels of analysis. The design of HRM policies as well as the implementation of HRM practices commonly occur at either an organizational, functional, departmental or group level whereas the behaviors and cognitions they seek to influence are located at the level of the individual employee (Bowen & Ostroff, 2004; Snape & Redman, 2010; Wright & Boswell, 2002; Wright & Nishii, 2007). Although multi-level techniques provide an avenue to test models with such hierarchical structures (e.g., Snijders & Bosker, 1999), they are developed for models where the outcome variable lies at the lower level of analysis. Problems arise when the outcome occurs at a macro-level (e.g., organizational performance) but the predictors reside at a micro-level (e.g., employee behaviors).

Scholars have creatively circumvented modeling such micro-macro processes. For example, studies relating HRM implementation and employee engagement to organizational performance have used three different approaches. Nevertheless, all three have their downsides. First, the micro-level scores can be aggregated to the macro-level. As such, studies have investigated HRM, engagement and performance at the level of the organization or the work group (e.g., Harter et al., 2002; Jiang et al., 2012; Subramony, 2009; Whitman, Van Rooy, & Viswesvaran, 2010). However, after aggregation to the macro-level, the data loses all information on individual variations (Bennink, Croon, & Vermunt, 2013). To illustrate, an aggregated team score of average engagement can be interpreted either as all employees in the team being averagely engaged, or as the team being a mix of highly engaged and highly disengaged employees. Moreover, aggregation has considerable consequences because the reduction of the sample size – to the size of the macro-level sample – significantly decreases the power of the statistical test (Bennink et al., 2013; Krull & MacKinnon, 1999). As a second approach, scholars have restricted the analysis to micro-level variables. For example, studies have examined employees' individual perceptions of HRM practices and its influence on employees' engagement and individual performance scores (e.g., Christian et al., 2011; Halbesleben, 2010). However, this approach introduces perspective bias as it looks at the impact of the perceptions employees have of the HRM strategies, policies, and practices. Moreover, no conclusions can be drawn regarding the impact on the actual organizational performance as the models have to rely on micro-level outcomes, such as individual performance evaluations. Finally, disaggregation has been a third approach, in which the macro-level scores (i.e., HRM and organizational performance) are assigned to each micro-level case (i.e., employee). Luckily, this method is not frequently found in published academic studies as disaggregating scores violates the assumption of independent error terms (Keith, 2005), causing biased standard error estimates, overly liberal tests (Krull & MacKinnon, 1999) and artificially high power (Bennink et al., 2013).

Bathtub models provide a solution that overcomes the problems specific to the aforementioned approaches by correctly modeling the multi-level processes at hand. They offer an opportunity to investigate the relationship between macro-level variables through micro-level mechanisms. Using a latent variable model, a bathtub model raises

micro-level responses to the macro-level while taking into account both within-group variance and sampling variability. Subsequently, the latent variable can be used as a regular predictor in the macro-level model. Applied to employee engagement, bathtub modeling provides an opportunity to examine how HRM policies and practices influence organizational performance through the behaviors of employees. This analysis can be conducted without ignoring the possibility that employee engagement is personal and individually determined (Macey & Schneider, 2008), and without inflating statistical power (Bennink et al., 2013, Krull & MacKinnon, 1999). The following illustrates the modeling process step-by-step. First, the data requirements are described, followed by the two parts of the model and their respective interpretation. Afterwards, several limitations to bathtub modeling are presented.

3.2.1 Data Requirements

Before conducting a bathtub model, the sample size and the data format need to be considered. The power of a bathtub model largely depends on the sample size at all levels of analysis. Hence, researchers should not only gather data of multiple groups but they should also ensure high response rates within the groups. Bennink (2014) demonstrates that a sample of as small as 40 groups with ten respondents per group can already result in nearly unbiased parameter estimates in case of a bottom-up, micro-macro effect (e.g., engagement on organizational performance). In order to detect more complex effects like interactions or indirect effects, larger sample sizes at the macro-level are required. Simulations demonstrate that 200 groups with ten respondents per group should be enough to detect most effects (Bennink, 2014), suggesting that increasing the macro-level sample size should be the focus for researchers seeking to examine small and/or complex effects.

After data collection, the bathtub modeling requires the data to be structured according to its multi-level nature. Depending on the statistical software used, the model can be estimated on a dataset with either a long or a wide format. For long datasets, each row would represent a micro-level case (e.g., employee) and one of the columns would identify the macro-level unit this micro-level case belongs to (e.g., team or work group). Subsequently, a bathtub model can be applied using a multi-level regression approach. For wide datasets, the format is more peculiar: each row needs to represent a macro-level unit whereas, for each micro-level case, each measurement should be stored in a separate column. This format is commonly referred to as the persons-as-variable approach and it does not work in all software packages (e.g., Mplus).

3.2.2 Bathtub Model

A bathtub model consists of two parts: a measurement model and a structural model. The measurement model describes the relationship between the observed micro-level (individual) variable(s) and the macro-level latent variable(s) based on them. Because this part of the model is primarily concerned with raising the individual-level scores to the group-level, it is often referred to as the within-group part. Next, the structural model describes the relationship between the variables at the macro-level. By relating the latent variable, derived from the measurement part, to the other macro-level

variables of interest, the bathtub model takes the individual variation that occurs at the micro-level into account. The below elaborates on both parts in more detail.

The measurement part of a bathtub model uses a multi-level latent variable model to raise the observed individual data to the level of the group. Here, the format of the individual, micro-level data is quite important. The latent variable approach was initially proposed by Croon and Van Veldhoven (2007), who demonstrated how treating individual scores as exchangeable indicators for a continuous latent variable makes it possible to predict a group-level outcome with lower-level independent variables. It works by estimating an unobserved continuous score at the group-level based on the observed individual data. Because the resulting latent group score reflects the underlying individual data and its variance, it takes the measurement and sampling errors that occur at the micro-level into account. However, this approach was developed specifically for raising continuous variables to the group-level using a normally distributed latent variable and, while very useful, the approach has the limitation that it cannot treat categorical variables adequately.

Bennink, Croon, and Vermunt (2015) therefore propose an extension of this latent variable approach, which makes it possible to raise categorical variables to the group-level using a generalized latent variable modeling framework (Skrondal & Rabe-Hasketh, 2004). This extended model allows micro-level discrete variables to be raised to the macro-level using a categorical latent variable, called a latent class variable. Using this approach, the unobserved heterogeneity at group-level can be estimated using a latent class variable that clusters together groups that are more similar to each other. In this way, individual data can be raised to the group-level by creating clusters of macro-level groups (i.e., latent classes) based on the similarity of their micro-level scores. Although it is common practice to have as many latent classes at the macro-level as there are discrete categories at the micro-level (Bennink, 2014), the optimal number of classes may also be estimated based on fit measures like BIC, AIC or χ^2. The strength of the measurement model can be assessed using the entropy (R^2), with values above .70 reflecting a strong model where classes are adequately distinguished (Vermunt, 2010). This latent class approach is especially useful in the social sciences. For example, in HRM research, the effects of categorical variables are often of interest (e.g., gender and educational level) whereas employee behaviors are often measured with categorical, ordinal measures (e.g., Likert-type items).

Once the measurement model is specified, the structural part of the model can be estimated. As the individual scores have been elevated in the measurement model, the structural model occurs completely at the macro-level and this is where the actual hypothesis testing takes place. Because it occurs on a single level, the interpretation of the structural model is comparable to that of a regular regression model, with direct, indirect and/or interaction effects depending on the specified model. The measurement scale of the dependent variable determines the type of regression model that applies (i.e., logistic, linear or ANOVA).

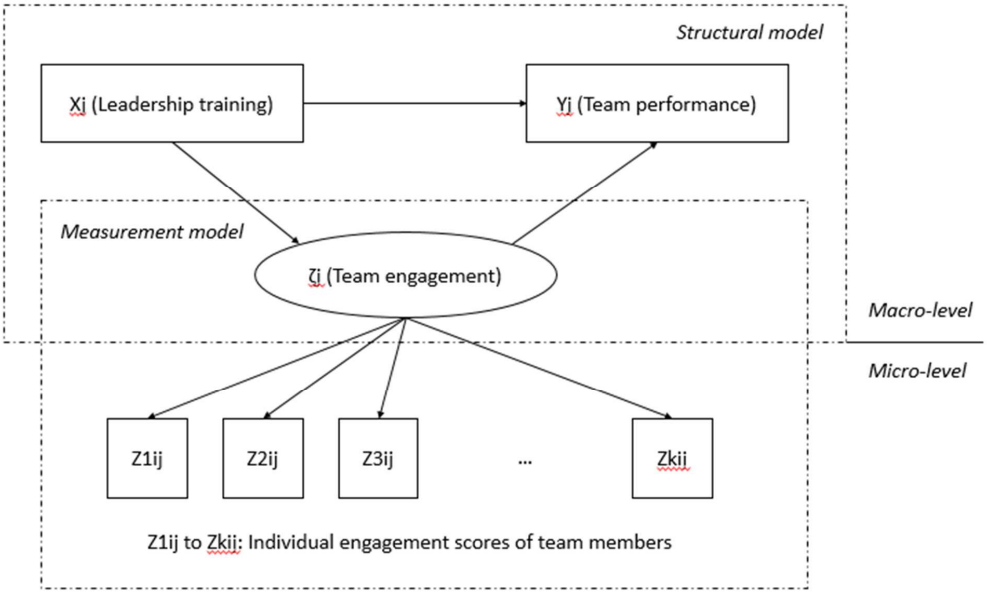

Figure 3.1: A bathtub model of the mediating effect of employee engagement in the relationship between leadership training and team performance.

To illustrate the above, imagine a study examining the effect of a specific HRM practice, hours of leadership training received by managers, on the performance of teams. The researchers might want to examine whether a part of this effect is indirect, for instance, via the engagement of employees. The bathtub model that corresponds with such a study is presented in Figure 3.1. Both the leadership training and the team performance occur at a macro-level and, therefore, their relationship can be estimated directly using a linear regression model at the group-level. In contrast, the engagement data is located at the level of the individual employee and thus requires elevation to the group-level using a bathtub model before its involvement can be examined. For this elevation, researchers can choose either a continuous latent variable model or a latent class model. A continuous latent variable would imply that group-level engagement scores run from highly disengaged up to highly engaged groups, following a normal distribution. A linear regression model could then be used to predict team performance, based on the leadership training and the continuous latent engagement scores. Alternatively, a latent class model could be applied. This would result in various macro-level classes and, subsequently, for each team, the probability that it belongs to one of the classes is estimated. For instance, one class could consist of teams where most individuals display an average level of engagement, whereas another class could be composed of teams with a few highly engaged and several disengaged team members. In contrast to an aggregation approach, the latent class model is able to differentiate between these two groups based on their different team dynamics. Afterwards, an ANCOVA model can be run at the macro-level, where team performance is explained by the leadership training and

the discrete latent group engagement scores. Finally, based on the output test statistics, the study's hypotheses can be confirmed or rejected.

3.2.3 Limitations of Bathtub Modeling

Micro-macro analysis in general and bathtub modeling in particular are innovative and well-performing approaches to examine how micro-level mechanisms influence the relationship between macro-level variables. However, there are several limitations.

For example, it is unclear how sample size influences the performance of bathtub models. Although Bennink (2014) demonstrates that the method generally outperforms the traditional aggregation and disaggregation approaches, the more complex bathtub models with indirect or interaction effects can provide equally inaccurate estimates when applied to small macro-level samples. While a sample of 200 groups should be sufficient to provide accurate results for complex models (Bennink, 2014), this number is quite large. The minimum sample size to establish accurate results is unknown and seems to differ from one model to the next. Furthermore, to date, no research has been conducted regarding power in bathtub models with continuous latent variables.

Additionally, it is unknown how missing values impact the performance of bathtub models. Although the standard approach to handling missing values in multi-level research is listwise deletion, multiple imputation is currently undergoing heavy development for the classical top-down effects (Van Buuren, 2011). The impact of missing values and the best way of handling them in multi-level research with bottom-up effects, such as bathtub models, has yet to receive empirical attention.

A further consideration lies in the person-as-variable approach, which considers the employees within a group as interchangeable. This approach implies that each individual within a group contributes equally to the estimation of the latent score for that group. For constructs like engagement, this seems theoretically sound as each employee's engagement can be considered equally important to the team's latent score. However, there may be HRM research questions in which the data of certain employees can be considered more important to or representative of the group's latent score. For example, when accounting for differences in employment type (e.g., full-/part-time or temporary/fixed contracts) or when scores follow specific distributions within subgroups of employees (e.g., forced distributed performance evaluations).

Although bathtub modeling clearly outperforms traditional aggregation and disaggregation approaches (Bennink, 2014; Bennink et al., 2013, 2015; Croon & Van Veldhoven, 2007), multi-level structural equation models (SEM) may function as an alternative. When the outcome variable resides at the micro-level, multi-level SEM can be preferable to bathtub models (Lüdtke et al., 2008). However, similar to the traditional micro-macro analysis (Croon & Van Veldhoven, 2007), a multi-level SEM only works with continuous data and is unable to handle categorical predictors. Additionally, multi-level SEM on continuous data frequently provides more biased estimates of the bottom-up effects than the latent bathtub model advocated by this paper (Onrust, 2015).

On a final note, bathtub models are very flexible and they run in most statistical software developed for latent variable modeling, including Mplus (Muthén & Muthén, 1998-2016) and Latent GOLD (Vermunt & Magidson, 2013). They can be conducted in R

(R Core Team, 2016) as well, using the *lavaan* package (Rosseel, 2012), but this requires some technical expertise. Similar to SEM, latent bathtub models can be extended to include multiple variables: both continuous and discrete latent variables, with single or with multiple response variables at the micro-level (Bennink et al., 2015). More detailed statistical descriptions of the model can be found in Croon and Van Veldhoven (2007) and Bennink and colleagues (2013, 2014) whereas a syntax for bathtub implementation in Mplus is provided by Bennink (2014).

3.3 Optimal Matching Analysis and Employee Engagement

The rapid development of HRM technology has initiated a trend towards the continuous measurement of personnel behaviors and cognitions. Mobile applications, social networks, sociometric badges, wearables, and continuous employee feedback systems are rendering more complex and longitudinal HRM data (Angrave et al., 2016; Bersin, 2015). Employee engagement is one of the constructs that organizations increasingly measure on such an ongoing basis, potentially because research demonstrates it is less stable than previously assumed. Although the work engagement employees experience is often regarded as a stable state of mind, with a dispositional element to it (Macey & Schneider, 2008; Schaufeli, Salanova, González-Romá, & Bakker, 2002), studies demonstrate that the explained variance among consecutive yearly measures ranges from a high 74% to a low 31% (Mauno, Kinnunen, & Ruokolainen, 2007; Schaufeli, Bakker, & Salanova, 2006; Seppälä et al., 2009). It seems that there is also a temporary, transient element to engagement, as employees report weekly and even daily fluctuations (Bakker & Bal, 2010; Llorens, Schaufeli, Bakker, & Salanova, 2007; Sonnentag, 2003).

In line with the above, researchers call for prolonged periods of observation with more frequent measurements of engagement. For example, Harter and colleagues (2002) conclude their meta-analysis of the Gallup engagement data calling for "*longitudinal designs that study changes in employee satisfaction-engagement, the causes of such changes, and the resulting usefulness to the business future research*" (p.276). Similarly, despite their relatively stable results, Seppälä and colleagues (2009) argue that "*longer follow-up with several measurement points would also allow investigation of the developmental trajectories of work engagement; utilizing a person-oriented approach would yield a more specific understanding of stability/change in work engagement than the conventional methods of the variable-centered approach*" (p.478).

HRM researchers have been using methodology other than GLM to examine longitudinal patterns for quite some time (Sanders et al., 2014), but optimal matching analysis (OMA) remains relatively unknown in the field. OMA is a quantitative method originating from the natural sciences, where it has been especially useful in detecting temporal patterns. The method works by assessing the similarity among longitudinal sequences, after which a user-specified unsupervised learning algorithm can be used to group the sequences based on their similarity. The result is a categorical variable representing the patterns hidden in the longitudinal data, which can be an insightful classifier on its own or can function as a predictor or outcome variable in further analysis.

OMA has several unique characteristics that make it an addition to the current methodological toolbox of HRM researchers. Similar to other longitudinal methods, OMA only requires a small sample and simulations demonstrate that results are still 95% accurate for samples as small as 50 employees (Dlouhy & Biemann, 2015). In contrast to other methods, however, OMA is a person-oriented method, meaning that the object under observation – the employee or team – is the focus of the analysis, rather than the variance in a specific independent variable (Abbot, 1988). This allows OMA to examine patterns on multiple variables simultaneously, which is a more complex assignment for other longitudinal methods, such as multi-level and latent growth models (Curran, Obeidat, & Losardo, 2010). Hence, OMA be used to examine employees' patterns on multiple dimensions of engagement (e.g., vigor, dedication and absorption; Schaufeli et al., 2002) or on engagement data coupled with other constructs. Additionally, OMA functions particularly well with the new forms of HRM data. OMA's classification results only increases with the number of nested observations (Dlouhy & Biemann, 2015) while other longitudinal methods soon require higher order polynomials to model observations over prolonged periods of time (Curran et al., 2010). Finally, despite the many observations and dimensions potentially included in OMA, it remains a relatively easy method to implement and interpret. To illustrate these advantages, the following section elaborates on a hypothetical study of weekly employee engagement data, like those gathered by a mobile application. The data requirements are described and afterwards each of the model steps is explained. Finally, several limitations and alternatives are discussed.

3.3.1 Data Requirements

OMA works by comparing cases based on their temporal sequences. These sequences consist of a string of elements, each reflecting the temporal state of the case at a specific moment in time. OMA handles these elements as categorical labels at this stage of the analysis, not recognizing any ordinal nature among them. Although this seems a disadvantage, it allows OMA to discover patterns in data that does not necessarily have an underlying order. For example, employees' trajectories across functions, locations, or organizational units (i.e., nominal or categorical variables) can be examined simultaneously with their engagement or performance levels (i.e., ordinal variables). While an order among elements can be assigned at a later stage of the analysis, at this time, it suffices to label each state with a unique element (e.g., working in finance, with high engagement, and high performance = 'A'). Once the elements are determined and labelled, OMA requires the input dataset to be transformed into a wide format, where each row represent a case and each column a measurement occasion, so that for each case a sequence of elements arises.

Missing values are common in longitudinal research but, compared to other methods, OMA handles them relatively easily. As long as no more than 30% of the elements within a sequence are missing, replacing missing values by an additional element (e.g., 'X' or '?') will result in a model performance that is nearly equal to that of a complete dataset (3% decreased classification accuracy in Dlouhy & Biemann, 2015). Although late joiners, attrition, and other factors may cause sequences to have different

lengths, OMA can handle these as long as the length of the shortest included sequence is at least 70% of that of the longest sequence. Nonetheless, specific sequences may contain more than 30% missing values. These sequences can either be deleted or, if missing values gather around the start or end of the sequences, the timeframe of observation can be shortened. However, both these approaches may introduce bias to the results and, as an alternative, researchers can decide to impute the missing values. Despite potential collinearity between sequential and missing elements, gap closure by recursive imputation has been demonstrated to provide accurate estimates of the missing data points (Halpin, 2012).

3.3.2 Penalty Costs

OMA determines the similarity between sequences based on the operations needed to align them – to make them similar. There are two types of operations that can be used to align sequences: *indel* and substitution. *Indel* is short for the insertion or the deletion of an element somewhere in the sequence whereas substitution refers to the replacement of an element by another element in that same exact place in the sequence. Both operations need to be assigned a penalty cost to reflect the dissimilarity the operation corrected, and especially the ratio between these respective costs is important (Aisenbrey & Fasang, 2010; Biemann & Datta, 2014). By default, OMA uses a standard indel-substitution cost ratio of 1:2, meaning that deleting an element and inserting another comes at the same penalty cost of a substitution.

This standard ratio implies that OMA views all underlying states as equally dissimilar. However, as discussed earlier, HRM research often uses ordinal variables, which imply that certain states are more similar to each other based on their place in the underlying order. To reflect this similarity, the penalty cost of substitutions between those states can be decreased. Such a decrease can be based solely on theoretical assumptions but, alternatively, the observed transitions in the actual data function as a basis. Here, the rationale is that the observed transition frequency between states provides information about the similarity between these states (Biemann & Datta, 2014).

To illustrate the above, assume three five-week sequences: E-E-E-E-E, representing a consistently engaged employee; N-N-E-E-E, representing an employee who went from neutral to engaged; and D-D-E-E-E, representing an employee who was disengaged for two weeks. Using the standard cost ratio, either sequence can be changed into the other at a penalty cost of 4: either by two element deletions and two element insertions, or by two substitutions. Alternatively, researchers could set theory-based substitution costs, penalizing transitions between states adjacent in the underlying order at a lower rate. For example, 1.75 for the adjacent levels of engagement whereas the standard 2 for more 'distant' levels. Subsequently, the penalty costs between the first and the last sequence in the above example would still equal 4 whereas those between the first two sequences and the last two sequences would now amount to 3.5. Data-based substitution costs would have the same effect if transitions between distant ordinal states occur less frequent.

Although setting custom substitution costs thus seems sensible, the approach has two downsides. First, substitution costs are not sensitive to the direction of a transition. Hence, Aisenberg and Fasang (2010) argue that custom costs should only be used "*if there*

is either a theoretical justification for the assumption that the costs are the same independent of the direction of the movement [...] *or if one of the directions is impossible*" (p.430). In HRM research, phenomena like positive and negative spirals (Fredrickson & Joiner, 2002) may, for instance, cause transitions towards the extremes of the engagement continuum to be more frequent than the other way around, invalidating this assumption of directional independence. Second, data-based substitution costs will reflect the within-sequence variability of elements and, therefore, the chosen timespan of elements has a strong influence. This becomes evident once applied to our engagement example. Assuming engagement fluctuates over time, element transitions would occur relatively frequent when longer-spaced timespans, like yearly measurements, are used. In contrast, element repetition would occur frequently in case of hourly observations. Both timespans have consequences for the data-based substitution costs and, while neither necessarily deteriorates results, researchers should consider that an interdependency exists.

3.3.3 Clustering the Sequences

Once the penalty costs are determined, the optimal matching algorithm can assess the (dis)similarity of each dyad of sequences by aligning them. Although there may be several ways to align two sequences, the algorithm seeks the one with the least penalty costs. As illustrated earlier, assigning custom substitution costs would thus make the algorithm more prone to use substitution. The process of sequence alignment is repeated for all dyads in the dataset and the resulting penalty costs are stored in a Euclidian distance matrix, named the dissimilarity matrix.

Next, a classification algorithm can be applied to the dissimilarity matrix. Any unsupervised learning algorithm that handles Euclidian distance matrices can be used. However, Dlouhy and Biemann (2015) "*do not recommend using k-means, median, centroid and single linkage clustering for OMA at all*" (p.171). Out of the eight techniques they tested, Ward's minimum variance method consistently performed best. Irrespective of the chosen algorithm, the result is a categorical variable where cases are assigned to a category based on the underlying patterns in their sequence. In the engagement example, employees will be grouped based on the patterns that have occurred in their weekly engagement levels. One can expect to find, for example, clusters of consistently disengaged, neutral, and engaged employees. Similarly, other clusters may include employees whose engagement has been steadily rising or falling, whose engagement demonstrates certain cyclical patterns, or whose engagement fluctuates randomly. Depending on the assigned penalty costs and the number of clusters, employees with missing values will be added either to the regular clusters or to clusters with specific, recurring patterns of missing values.

OMA's output can be valuable to researcher and practice in at least four ways. First, OMA's relatively simple implementation and interpretation makes it an effective tool to get descriptive insights in longitudinal data patterns. Second, OMA can be useful for identification purposes. For example, based on the cluster output, researchers can effectively identify which employees display certain (dis)engagement patterns and reach out with follow-up interviews or (supportive) interventions. Third, the output can be used as an independent variable in subsequent analyses to study the consequences of following

a specific pattern. For example, the displayed engagement patterns could function as predictor in leadership, performance, or attrition models. Fourth and final, the cluster output can function as dependent variable for subsequent analysis regarding pattern occurrence. For example, individual differences or HRM practices may explain why certain employees are more likely to display particular engagement patterns.

3.3.4 Limitations of OMA

A general shortcoming of OMA is that it aims to summarize a database filled with potentially very complex sequential patterns into a (handful of) categorical variable(s). While this has proven useful in certain research fields – including research on DNA, life courses, and careers – it has yet to be tested whether longitudinal measures of employee behaviors and cognitions can be similarly reduced to a set of patterns.

A second challenge relates to setting the substitution costs right. Several studies illustrate how this ratio should be matched to the specific requirements of the research question and the analysis (Hollister, 2009; Lesnard & Kan, 2011). Other scholars have argued that standard and custom cost ratios lead to similar conclusions (Biemann & Datta, 2014). No study provides insights regarding the optimal settings for research on employee experiences, which may be affected by a wide variety of personal and institutional factors. Moreover, there are rightful concerns regarding the symmetrical nature of the substitution costs (Aisenbrey & Fasang, 2010) which causes transitions between states to be regarded as similar, irrespective of their direction. There seems to be no simple solution to the aforementioned issues, apart from some general best practices regarding the cost setting procedure (e.g., Gauthier, Widmer, Bucher, & Notredame, 2009).

A third limitation lies in the descriptive nature of OMA. The method can reduce large information volumes into smaller, workable sets of underlying patterns and complementary analysis may provide insights into why these patterns occur and what they result in. However, researchers seeking to test why, how and when patterns occur and trajectories develop may turn to other methods. Here, multi-level and latent growth models can be used to examine the rate of pattern development as well as its causes. Additionally, hazard and Markov models may uncover why and when transitions between states happen. Moreover, time series analysis could be applied to investigate reoccurring patterns and forecast the future state of employees.

Finally, the only software that currently provides a means for automated implementation of OMA is R (R Core Team, 2016). The *TraMineR* package (Gabadinho, Ritschard, Müller, & Studer, 2011) contains functions that automate the process to a large extent and only minor specification and customized programming is required. Additionally, the package includes several visualization functions that facilitate the interpretation of the model's output. However, getting accustomed to the R language and syntax can be effortful.

3.3.5 Discussion

Previous research has heavily relied on GLM to investigate HRM processes and their potential impact on performance. This paper proposes two statistical modeling

techniques that, despite their novelty to the field, can be valuable additions to the methodological toolbox of HRM researchers and practitioners. Particularly in light of the growing need to justify, prioritize, and improve decision-making (Boudreau & Ramstad, 2007; Rasmussen & Ulrich, 2015; Ulrich & Dulebohn, 2015) and the new forms of HRM data that arise due to technological developments (Angrave et al., 2016; Bersin, 2015). Using latent variables, bathtub models are put forward as the solution to examine multi-level mechanisms with outcomes at the team or organizational level without decreasing the sample size or neglecting the variation inherent in employees' responses to HRM activities. Optimal matching analysis is proposed as particularly useful to examine the longitudinal patterns that occur in repeated observations over a prolonged timeframe. Research on employee engagement was used to illustrate how each method functions and how they add value over and above the current methods used in HRM research.

Although both bathtub modeling and OMA both elevate micro-level data to a macro-level, the two methods strongly vary in their purpose, in their complexity, and in the expertise required to implement them. The application of OMA does not require deep statistical or conceptual knowledge and the pattern visualizations facilitate an easy interpretation. However, this simplicity is also reflected in the primarily descriptive insights the method provides. In contrast, the underlying equations as well as the output of bathtub models may be harder to explain to laymen such as business and HRM professionals (see Bennink et al., 2013, 2014; Croon & Van Veldhoven, 2007). This increase the difficulty that scholars and HRM analytics professionals may experience in translating the latent variable model's results into actionable insights for decision-makers.

Nevertheless, both techniques can add value to HRM research on a variety of themes, either applied separately or in synergy with each other and other methods. Recruitment and selection is one field of potential future application. OMA has been frequently applied on career patterns (e.g., Blair-Loy, 1999) and, similarly, by clustering applicants based on their prior work experiences, the method could be valuable for selection purposes. For example, applicants' historic job positions can be coded into unique states based on the associated management responsibilities or the required level of technical expertise. The required 25 months of input data for OMA (Dhouly & Biemann, 2015) could be extracted directly from applicants' résumés, but the digital job market becomes an ever-richer data source as well (e.g., LinkedIn, Xing, ResearchGate). The resulting clusters may facilitate decision-making in the selection process, similar to applicants' assessment center scores, interviewer ratings, and other recruitment data. Additionally, a latent bathtub model could use such data to examine the effectiveness of recruitment, selection and/or socialization practices. Irrespective of these practices, bathtub models could also investigate whether certain (combinations of) applicant profiles improve the effectiveness of teams.

The methods may additionally be valuable with regard to workforce planning, facility management, and flexible working arrangements. Recent work by Lesnard and Kan (2011) demonstrates how a two-stage OMA can be used to first cluster the daily work schedules of employees, and subsequently use these clusters to unveil the patterns

employees display in their weekly schedules. Using the data collected by sociometric badges and '*smart*' workplaces, HRM scholars and practitioners could use OMA to uncover patterns in the use of office spaces over time or across locations. This may have direct practical value in terms of the cost reductions related to facility management, but may also be insightful for the design of flexible work arrangements. Moreover, certain configurations of work schedules within teams may have a detrimental impact on their effectiveness. This could be examined by using the cluster output of OMA in subsequent bathtub models, raising the work schedules to a team-level and relating them to team performance.

Furthermore, talent management research may benefit from OMA and bathtub models. Contemporary organizations often focus their attention on a small group of employees labeled with high leadership potential (so-called "HYPO's"), consistent with the literature on Paretian performance distribution (O'Boyle & Aguinis, 2012). OMA could model the history of job positions that distinguish such HYPO's from other employees. Moreover, one could examine whether receiving the status of HYPO influences the developmental opportunities employees get in the period that follows. The characteristics of the clusters derived by an application of OMA to such research questions can be directly valuable for the design of talent management policies and practices. Moreover, the cluster output may function as input data for further analysis examining the causes and results of cluster membership. With or without the cluster information, bathtub models could examine how talent management policies affect individual employees and, in turn, organizational performance. Moreover, bathtub models could examine which HRM practices stimulate the development of employees in general, and HYPO's in specific, and whether this development contributes to the achievement of business goals. Finally, irrespective of HRM implementation, a latent variable model could be used to examine whether the presence of HYPO's in a team influences team effectiveness.

Finally, the flexibility of latent variable models makes it a valuable tool to examine a wide variety of contemporary HRM themes. For example, latent approaches can also be used to model unobserved heterogeneity between respondents. This can be valuable to HRM research on team diversity, for example, in terms of location, tenure, age, gender, or cultural background. A more abstract example lies in the investigation of team heterogeneity in terms of individual psychological contracts (e.g., Bakk, Tekle, & Vermunt, 2013). Similarly, the data of e-mail traffic or sociometric badges can be used to examine heterogeneity in terms of the personal networks employees have. Subsequently, the impact of such heterogeneity on the development, retention, or performance of individuals, teams, and organizations could be assessed. Combined with OMA, this latent heterogeneity of teams could be monitored over longer periods of time to see whether improvement occurs, potentially as a result of changes in HRM policies. Moreover, latent variable models can be used to grasp constructs that are otherwise hard to measure. For instance, a latent performance score could be estimated using multiple indicators of employee's behavior or job output. This latent score has the potential to be a more accurately reflection of employees' actual performance than the separate indicators or their combined average (Murphy, 2008).

In conclusion, bathtub models and OMA can add value on many HRM themes, allowing an investigation of research questions that were previously hard to examine. The methods can stimulate the quality of decision-making either by offering a different analytical approach to the issue at hand, or by working in synergy with each other and more traditional HRM methodology. Bathtub modeling and OMA are just two examples of methods that are common in other research fields and can benefit the HRM community. We hope that, by demonstrating how these specific methods add value in analyzing the new forms of HRM data, HRM researchers and practitioners become more open to methodological developments in- and outside the field of HRM. In the end, alternative methodology can offer a different perspective and facilitate improved, more objective decision-making regarding human capital.

4 Expatriate support and success: A systematic review of organization-based sources of social support

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This paper reviews empirical research on the relationship between organization-based social support and the success of international assignments. Four search engines were used to obtain empirical studies relating organization-based social support to success criteria. Studies were compared based on their theoretical foundation, on criteria of success, on sources of social support, and on study design. The reviewed studies draw on three theoretical paradigms – based on stress, social capital and relational exchange. The results demonstrate that expatriates receive social support from multiple organization-based sources and that these sources' proximity to the expatriate influences the relationship between social support and success. Moreover, results suggest sources in the home and host countries fulfil different supportive functions and therefore stimulate different success criteria. Additionally, the supportive practices offered by the organization can influence various criteria of success. The impact of support from organizational members is further influenced by their hierarchical proximity to the expatriate, with supervisory support relating most strongly to success. In addition to proximity, characteristics of the expatriating employee and the assignment (e.g., expatriate motivation and assignment hardship) influence the value of social support. Finally, social support relates most strongly to expatriates' satisfaction, commitment, and adjustment and these frequently mediate its effect on expatriates' retention and performance.

4.1 Introduction

The transition implied by an international assignment (IA) often brings about situational uncertainty and elevated job demands for the expatriate, who simultaneously needs to leave behind most of his/her professional and personal social networks. Overseas transfers may therefore have serious consequences for expatriates' well-being, adjustment and performance in their new roles (Baruch et al., 2016; Black et al., 1991). An expatriate's social environment can, however, provide the necessary resources that allow him/her to address this transition (Adelman, 1988; Caligiuri & Lazarova, 2002; House, 1981; Lin, 1999).

Social support from within organizations is widely acknowledged as crucial to the success of IAs (see Bhaskar-Shrinivas et al., 2005), but several factors seem to moderate its impact. First, expatriates distinguish among different sources of organization-based social support and these vary in terms of their impact on IA success (Kraimer & Wayne, 2004; Kraimer et al., 2001). In part, this may be due to the (perceived) proximity between the source of support and the expatriate (Altman & Taylor, 1973; Byrne, 1971; Ibarra, 1992). This proximity can be hierarchical, geographical, situational and/or cultural, and determines, among other things, the frequency and formality of contact, the content and mode of interaction, the shared (overseas work) experiences and the (perceived) cultural gap (Claus et al., 2015; Gudykunst & Nishida, 2001; Johnson et al., 2003; Ng & Sorensen, 2008). Second, the context in which the social support is provided can affect its value. On the one hand, the value of social support may increase with the demands of the IA (Bakker et al., 2007). On the other hand, social support can be less valuable when substitutes are available, such as assistance from other sources (see Podsakoff et al., 1996).

Multiple criteria have been used to measure the success of IAs. In general, the effect of social support seems stronger when evaluated using more "proximal" criteria (Harrison & Shaffer, 2005), but studies show that the moderating factors described above introduce exceptions. For example, social support by supervisors directly stimulates distal criteria such as expatriate performance and retention, whereas organizational support has its effect through processes of adjustment and commitment (e.g., Kraimer & Wayne, 2004; Kraimer et al., 2001).

This paper examines how these moderating factors have influenced the relationship between organization-based social support and the success of international assignments. This may provide clarity regarding which criterion of international success is affected by which type of assistance, by whom, and under which conditions. Such clarity holds value for both academia and practice. Future expatriate management research may be aided by understanding the factors that need to be taken into account when investigating social support. Moreover, this review may provide insights into the (causal) relationships between social support and proximal and distal success criteria. In terms of practical value, this review provides a basis of evidence for the decisions human resource and global mobility professionals need to make regarding the implementation of practices and policies. In particular, the insights of this study may shed light on the optimal design of the overseas transfer and socialization process. Based on the results, organizations may

wish to tailor their supportive practices to expatriates as well as assignments in order to increase the effectiveness and the return on investment of the provided support.

4.2 Search Methodology

In September 2015, we systematically searched the libraries Web of Science (Core Collection); EBSCOhost (Business Source Elite, PsycARTICLES, PsycINFO, Psychological and Behavioral Sciences Collection); ProQuest and ScienceDirect for relevant documents. Twenty-one keywords had been derived from literature and through discussion with international human resources and expatriate management scholars in the authors' networks. Clustered into three subgroups, these keywords resulted in 100 possible keyword combinations for which titles, abstracts and subject terms of documents were searched (Table 4.1). In addition to the automated search, all issues of the Journal of Global Mobility published prior to September 2015 were manually inspected for additional relevant studies by examining their abstracts and full texts.

4.2.1 Inclusion Criteria

The automated search resulted in 854 references, of which 572 were unique. Of these, 78 references were excluded because they were not written in English (2), did not refer to an academic study (22), or no full text was available (54). Next, studies had to examine expatriates in a professional environment. This led to the exclusion of 225 documents that studied regular employees, missionaries, soldiers, partners, students or repatriates, or that did not study a work context. Another 171 documents were excluded because they did not examine success criteria. Following Caligiuri (1997) and Harrison and Shaffer (2005), expatriates' adjustment, commitment, performance, and retention (including return intentions) were considered relevant criteria of IA success for this literature review. Expatriates' satisfaction was added as a fifth success criterion because scholars regard it as a proxy for the mediational process between social support and success (e.g., Cao et al., 2014). Finally, 36 documents were excluded because they did not examine social support. Of the remaining 64 documents, 37 were empirical studies examining how social support in expatriates' work environments influences at least one of the criteria named above. A manual search of the Journal of Global Mobility resulted in the identification of two additional studies that met the inclusion criteria. The final selection therefore yielded 39 articles, including three doctoral dissertations (De Paul Chism, 2014; Littrel, 2007; Pattie, 2007). Please refer to Table 4.2 for an overview of the selection process.

Table 4.1: Keywords by their respective cluster.

Social support	Expatriate success	Specificity of sample
support	performance	expat*
	effectiveness	sojourn*
	success	inpat*
	failure	transpat*
	attrition	country national*
	retention	global professional*
	intent*	global worker*
	cognition*	overseas assign*
	withdraw*	international assign*
	commitment	global assign*

Note: An asterisk (*) means that the keyword was truncated and thus extended versions of that keyword were also included.

Note: One hundred (1 x 10 x 10) keyword combinations were used.

Table 4.2: The seven steps in the selection procedure.

	Specification	Remaining studies	Excluded studies
Search results	Web of Science	854	289
	EBSCO		368
	ProQuest		139
	ScienceDirect		58
1st step	Unique studies (automatic)	764	-90
	Unique studies (manual)	572	-192
2nd step	Full text English articles	496	-76
3rd step	Expatriate sample	271	-225
4th step	Success criteria	100	-171
5th step	Social support	64	-36
6th step	Empirical papers	37	-27
7th step	Manual search of JGM	39	2

4.2.2 Coding

The 39 studies were then coded by the first author on four dimensions. First, it was determined which theories the articles had used to explain how social support may relate to the success of IAs. The mentioned theories clustered in three paradigms and articles were coded according to which of these they had used. Second, the success criteria examined by the articles were coded. Third, social support was coded according to the characteristics of its source. A basic distinction was made between organizations and their members. These members were furthermore coded for their proximity to the expatriate in terms of organizational hierarchy (i.e., supervisor, mentor, peer or subordinate), their geographical location (i.e., located in the home or host country), their employment status (i.e., host country national, inpatriate or expatriate) and their cultural background (same or different from expatriate). Finally, study design elements were examined, such as sample characteristics, the measures used and their raters.

4.3 Theoretical Paradigms

In the broadest sense, social support can be defined as the assistance and protection that one party provides to another (Shumaker & Brownell, 1984). More specifically, scholars have proposed that social support manifests itself in four types or forms. Emotional support is the affective component of social support and involves the provision of care, empathy, love and trust. Instrumental support consists of more concrete assistance, in the form of tangible resources, services or aid. Informational support relates to the provision of information to assist with general problem-solving. Finally, appraisal support involves the provision of information for self-evaluation (House, 1981). Multiple theories link social support to the success of IAs and the theories used by the 39 articles in this review can be clustered into three theoretical paradigms: a stress, a social capital and a relational paradigm.

First, ten articles (26%; Table 4.3) refer to theories on stress management. International assignments imply major transitions in terms of work and living environment, job content, work roles and/or employment status. Such changes can be stressful and threatening as they introduce considerable uncertainty (Ashford & Taylor, 1990). For example, the behavioral patterns associated with the new culture in general and the new work role in particular may not be clear and may thus cause stress (Kahn et al., 1964; Katz & Kahn, 1978). Additional uncertainty may arise because of changes in non-work roles due to the overseas transition (Minuchin, 1974), and the resulting strain may have implications for an expatriate's work environment as well (Lazarova et al., 2010). In summary, the general notion of theories in the stress paradigm is that an IA causes stress and adjustment issues due to uncertainty, which can be minimized by providing expatriates with resources through social support (Ashford & Taylor, 1990; Gudykunst & Nishida, 2001).

Second, ten articles (26%; Table 4.3) use social capital, social networks and social learning theories to demonstrate how an expatriate's professional network can stimulate IA success. According to social capital theory, an expatriate's social network holds certain resources that can be accessed by the expatriate (Lin, 1999). This means that expatriates can call on their social ties for assistance, including financial or material benefits, emotional support, task assistance, information, visibility, legitimacy and/or sponsorship in a social system (Seibert et al., 2001). By mobilizing this social capital, expatriates make sense of, behave appropriately and perform effectively in their work environment. This relates to social learning theory (Bandura, 1977), which posits that expatriates learn how to behave in their new cultural and work environment by observing and interacting with their social ties. In this sense, expatriates gain information about their expected role and work behaviors and about the cultural norms and social conventions of the host country through interactions with their colleagues (Aycan, 1997; Black et al., 1991; Caligiuri, 2000). Altogether, this "social capital" paradigm proposes that expatriates draw resources from their professional social networks, which allows them to behave effectively in their overseas environment.

Third, seventeen studies (44%; Table 4.3) refer to theories based on relational exchange and psychological contracting. In general, social support can be viewed as a

resource that is shared with the expectation of reciprocity (Cohen & Syme, 1985) and, therefore, exchange theories argue that interactions between two parties create a pattern of mutual obligation (Blau, 1964; Gouldner, 1960). For example, expatriates form an exchange relationship with their employing organization(s). Organizational support theory therefore posits that, based on the policies and practices in place in an organization, an expatriate may infer to what extent the organization(s) support(s) his/her well-being. The more supported the expatriate perceives him-/herself to be, the more s/he will reciprocate that support regarding the good of the organization and its members (Rhoades & Eisenberger, 2002). This process closely links to theory on psychological contracts, which involves the expectations of employees and organizations regarding their mutual obligations to each other (Rousseau, 1995). However, expatriates also perceive such an exchange relationship with their leaders (i.e., their supervisors). An expatriate with a high-quality leader-member exchange relationship will build mutual respect and loyalty over time through the reciprocal exchange of supportive resources with his/her supervisor(s) (Liden & Maslyn, 1998). The care and assistance these expatriates perceive themselves as receiving from their supervisors may, by itself, increase their ability to be successful. However, expatriates may return the favor to their supervisors by showing higher levels of affection and effort. In conclusion, this "relational" paradigm proposes that expatriates receive support from their work environment and feel obliged to reciprocate with effort and psychological bonding.

In sum, the 39 studies in this review have used stress, social capital and relational paradigms to explain how social support may relate to IA success. The remainder of this review first examines the support that expatriates perceive themselves to receive from their organization(s), before turning to the assistance expatriates receive from three hierarchical groups of organizational members (i.e., supervisors, mentors and co-workers). Each separate section elaborates on the relationship between social support from one source and the five success criteria. Moreover, each section presents source-specific moderating factors and an intermediate conclusion. The overall conclusions and implications for future research and practice are presented in the final discussion section.

Table 4.3: Included articles, their theoretical frameworks and the examined variables.

Authors (year)	Theoretical paradigms			Support constructs	Success constructs				
	Stress	SC	RE		S	C	R	A	P
Bader & Berg, 2013				HCN disaffection					1
Bader et al., 2015	X			POS					1
Benson & Pattie, 2009			X	Host supervisor LMX; Home supervisor LMX			1	2	1
Bhatti et al., 2013	X			Direct and indirect support				3	1
Bozionelos, 2009				Protégé experience; peer support	1		1		
Bruning et al., 2012			X	HCN colleague; HCN network size; HCN network frequency; HCN network density; HCN network closeness				1	1
Cao et al., 2014		X	X	POS; career network size with HCNs; career network size with home country nationals	1		1		
Chen et al., 2010				Subsidiary support				1	1
Chen, 2010			X	Perceived organizational supports; LMX				1	
Chen et al., 2011	X			Group support; Workmate support; Support from motherland				1	1
Claus et al., 2015		X		Support network size; virtual contact; frequency of contact				4	
De Paul Chism, 2014[1]			X	Host POS; Home POS			2	1	
Florkowski & Fogel, 1999			X	Realistic assignment preview; relative standard of living;		2	1	1	

Authors (year)	Theoretical paradigms			Support constructs	Success constructs				
	Stress	SC	RE		S	C	R	A	P
				home-country mentor; repatriation policy					
Guzzo et al., 1994			X	Financial inducements; general support; family-oriented support; financial sufficiency; general support sufficiency; family sufficiency; POS work; POS off the job; POS repatriation		1	2		
Harrison & Shaffer, 2005	X			Leader-team exchange				3	2
Jayasekara & Takahashi, 2014				HRMPs (preparation; recruitment; selection; training; performance evaluation; compensation)		2	1		
Johnson et al., 2003		X		Number of expatriate contacts; Number of HCN contacts; Breath expatriates (x3); Depth expatriates (x3); Breath HCN (x3); Depth HCN (x3)				3	
Kawai & Mohr, 2015	X		X	POS; PSS	1			1	1
Kawai & Strange, 2014			X	Career POS; Finance POS; Adjustment POS		1		1	1
Kraimer & Wayne, 2004			X	LMX; Adjustment POS; Career POS; Financial POS; Global POS		2	1	1	2

Authors (year)	Theoretical paradigms			Support constructs	Success constructs				
	Stress	SC	RE		S	C	R	A	P
Kraimer et al., 2001	X	X		Parent company POS; Foreign facility POS; LMX				3	2
Lee & Kartika, 2014	X	X		Organizational support;				1	
Littrell, 2007[1]		X		Psychosocial peer support (home/host); Career peer support (home/host); Mentoring peer support (home/host); Number of home country mentors (x2); Number of HC mentors (x2); Total number of mentors	5		2	1	
Liu & Ipe, 2010			X	Parent company POS; Local subsidiary POS; LMX		1			
Malek et al., 2015	X		X	POS				1	1
Pattie, 2007[1]				PSS; LMX			1		1
Pattie et al., 2013			X	LMX			1		1
Puck et al., 2008		X		Support; Rewards	1	1	1		
Shaffer et al., 2001		X		POS			1		
Shen & Jiang, 2015				POS					1
Shih et al., 2010				HIWS (HR flow; work structuring; reward systems; employee influence)	1				1
Showail et al., 2013				POS					1
Stroppa & Spieß, 2011				Co-worker social support; Supervisor social support	1				1
Supangco & Mayrhofer, 2014	X	X		POS; Supervisory support	1			1	
Takeuchi et al., 2009	X		X	Current assignment POS; Off-the-job life POS		1		2	1
Van der Heijden et al., 2009			X	Career POS (parent)			1		2

Authors (year)	Theoretical paradigms			Support constructs	Success constructs				
	Stress	SC	RE		S	C	R	A	P
Wang & Takeuchi, 2007		X		POS			1	3	1
Wu & Ang, 2011			X	Company support			1	3	2
Yahya et al., 2012			X	POS		3			
Count (39)	10	10	17		8	9	16	22	23
Percentage	26%	26%	44%		21%	23%	41%	56%	59%

Note: SC = Social capital; RE = Relational exchange; S = satisfaction; C = commitment; R = retention; A = adjustment; P = performance; X = applicable; 1-4 = number of dependent variables.

[1] Doctoral dissertation

4.4 Organizational support

Following the domestic literature (e.g., Rhoades & Eisenberger, 2002), organizational support encompasses all those practices and policies that are perceived by expatriates as conveying that the organization(s) values their contributions, cares about their well-being, considers their goals and values, treats them fairly, listens to their problems and helps to solve them. Prior studies have identified up to 43 such practices that organizations can implement to facilitate international assignments and to stimulate the social support expatriates perceive to be coming from the organization (Guzzo et al., 1994).

Twenty-six studies in the current review have investigated perceived organizational support (POS) using different measures. Seventeen studies examined expatriates' perceptions regarding the general supportiveness of organizations (e.g., Shaffer et al., 2001). Alternatively, four studies examined POS in terms of the specific practices implemented by organizations (Florkowski & Flogel, 1999; Jayasekara & Takahashi, 2014; Shih et al., 2010; Wu & Ang, 2011), whereas another four examined specific types or bundles of practices (Kawai & Strange, 2014; Kraimer & Wayne, 2004; Puck et al., 2008; Van der Heijden et al., 2009). Guzzo et al. (1994) investigated both general POS as well as specific practices and found that the effect of practices on IA success is indirect through expatriates' general POS.

4.4.1 Organizational Support and Success

The 26 studies demonstrated that POS is highly important for the success of IAs. In particular, the positive effect of POS on the more proximal success criteria is apparent. POS consistently has a positive effect on the job satisfaction and organizational commitment of expatriates (Cao et al., 2014; Guzzo et al., 1994; Jayasekara & Takahashi, 2014; Kawai & Strange, 2014; Kraimer & Wayne, 2004; Liu & Ipe, 2010; Puck et al., 2008; Shaffer et al., 2001; Takeuchi et al., 2009; Shih et al., 2010; Supangco & Mayrhofer, 2014; Yahya et al., 2012). Similarly, positive relationships with expatriates' adjustment were found in the majority of studies (Bhatti et al., 2013; Kawai & Mohr, 2015; Kawai & Strange, 2014; Kraimer & Wayne, 2004; Kraimer et al., 2001; Malek et al., 2015; Takeuchi et al., 2009; Wu & Ang, 2011; Wang & Takeuchi, 2007). Only three studies found nonsignificant effects of POS on adjustment. While Chen et al. (2010) likely found no effect due to their aggregated measure with low power, an effect of POS in Chen (2010) and Supangco & Mayrhofer (2014) may have been absent due to the support from alternative sources that was included in their models.

POS consistently has a positive effect on the more distal success criteria, but the observed relationships are frequently indirect. Regarding the completion of assignments and the retention of expatriates, eleven studies demonstrated a positive effect of POS. However, combined, their results suggest that this effect is not only direct but also partially indirect through the adjustment, satisfaction and commitment of the expatriate (Cao et al., 2014; De Paul Chism, 2014; Florkowski & Fogel, 1999; Guzzo et al., 1994; Jayasekara & Takahashi, 2014; Kraimer & Wayne, 2004; Puck et al., 2008; Shaffer et al., 2001; Van der Heijden et al., 2009; Wang & Takeuchi, 2007; Wu & Ang, 2011).

The results of the fifteen studies that investigated POS in relation to expatriates' performance are less straightforward. Four suggest a direct positive link (Malek et al., 2015; Shen & Jiang, 2015; Shih et al., 2010; Wu & Ang, 2011), five found no effect of POS at all (Bader et al., 2015; Chen et al., 2010; Kawai & Mohr, 2015; Showail et al., 2013; Wang & Takeuchi, 2007) and, finally, five studies found that the effect of POS on expatriate performance is mediated by expatriates' satisfaction, commitment and adjustment (Bhatti et al., 2013; Bader & Berg, 2013; Kawai & Strange, 2014; Kraimer et al, 2001, 2004). Only one of the studies that investigated the direct effect also tested for indirect effects and found partial mediation (Malek et al., 2015). It is likely that the larger part of the effect of POS on expatriate performance occurs indirectly through the more proximal success criteria.

4.4.2 Moderating Factors

This review found three main factors that can moderate the impact of organizational support on the various criteria of IA success. The first relates to the type or content of the support provided, the second to the geographical proximity of the organizational entity providing the support, and the third to the context in which the support is provided.

First, there are many practices that organizations can implement to assist their expatriates (see Guzzo et al., 1994), and expatriates may therefore feel more or less supported in different aspects of the expatriation process. While earlier studies investigated the effects of individual practices, contemporary research more frequently examines how expatriates' feel supported in these different aspects, including their career, their adjustment and their finances. Career POS is defined as "the extent to which the organization cares about the employee's career needs" (Kraimer & Wayne, 2004, p218) and has been shown to relate directly to expatriates' commitment, their adjustment and their intentions to complete the assignment (Kawai & Strange, 2014; Kraimer & Wayne, 2004; Van der Heijden et al., 2009). However, the positive effect of career POS on performance seems to be indirect (Kawai & Strange, 2014; Van der Heijden et al., 2009). Adjustment POS refers to the extent to which the organization cares about the adjustment of the expatriate (and his/her family) following the overseas transfer (Kraimer & Wayne, 2004). Adjustment POS relates positively to expatriate adjustment but may actually have a negative effect on the performance of expatriates (Kraimer & Wayne, 2004). Finally, financial POS is defined as "the extent to which the organization cares about the employee's financial needs and rewards the employee's contributions in terms of compensation and employment benefits" (Kraimer & Wayne, 2004, p218). Apart from enhancing expatriates' satisfaction and commitment, financial POS has a direct positive effect on expatriates' retention and performance (Jayasekara & Takahashi, 2014; Kraimer & Wayne, 2004; Puck et al., 2008). In sum, the type of support provided to expatriates may influence whether or not certain success criteria are influenced (directly). Most strikingly, financial support stimulates expatriates' performance directly whereas career assistance may only have an indirect effect, and adjustment POS may even have negative consequences for expatriates' performance.

Similar conclusions may be drawn based on an early study that examined the effects of a realistic assignment preview, financial support, home country mentoring, and a clear

repatriation policy (Florkowski & Fogel, 1999). Its results demonstrated that financial support particularly stimulated commitment and expatriates' intentions to remain on the assignment. Furthermore, a clear repatriation policy was beneficial for expatriates' commitment to the parent organization but decreased their commitment to the subsidiary. Home country mentoring and realistic previews had no effects on expatriates' adjustment, commitment or leave intentions. Again, these findings highlight that the impact of organizational support seems to depend on the type or content of the support and the criteria of IA success under investigation.

Multiple organizational units share the responsibility to provide support during IAs, introducing a second moderating factor. At least two organizational units are involved in the expatriation process: a sending parent organization and a receiving host subsidiary organization. While scholars acknowledge that expatriates are in a dual employment relationship – involving psychological contracts with both the parent and the subsidiary organization – this has not frequently been accounted for in empirical investigations of organizational support. Only three out of 26 studies in this review have examined whether it matters which of the organizational units is considered the provider of support. These studies demonstrate that support by each unit has distinct value for the commitment (Liu & Ipe, 2010) and adjustment of expatriates (Kraimer et al., 2001) but that expatriate retention is only stimulated by support from the parent organization (De Paul Chism, 2014). This raises questions regarding the referent organization(s) in the other 23 studies as well as regarding the relationship between parent and subsidiary POS and the other success criteria.

The third moderating factor involves the context in which the support is provided. Organizational support may be more or less valuable depending on the assignment context and the expatriate him-/herself. Regarding assignment contexts, on the one hand, the value of social support seems to increase with the level of hardship. For example, the effect of POS on expatriate performance was stronger under conditions of high stress (Bader et al., 2015), high demands (Kawai & Mohr, 2015) and local prejudice (Shen & Jiang, 2015). On the other hand, the value of social support may be affected by the availability of supportive resources in general. For example, synergetic (Liu & Ipe, 2010; Takeuchi et al., 2009), complementary (Kraimer & Wayne, 2004; Kraimer et al., 2001; Supangco & Mayrhofer, 2015) and substitution (Chen, 2010; Shen & Jiang, 2015; Supangco & Mayrhofer, 2015) effects have been found between different forms of social support from different sources. Regarding individual differences, the value of support may vary from one expatriate to the other. For instance, POS only stimulated performance among expatriates who identified with their organization (Showail et al., 2013).

4.4.3 Conclusion

In conclusion, POS typically has a positive impact on the success of IAs. It has a direct positive influence on more proximate success criteria, such as expatriate satisfaction, commitment and adjustment. The effect of POS on the retention of expatriates and the completion of assignments is also positive but may be partially indirect. Regarding the performance of expatriates, the impact of POS is typically indirect, although direct effects were found if the assistance involved financial support or was provided under certain

circumstances. Finally, the assistance provided by parent and subsidiary organizations can have unique, differential and/or synergetic effects. Further implications for POS in research and practice are presented in the discussion section.

4.5 Support by Organizational Members

Separately from the organization, organizational members can function as a source of social support for expatriates. These organizational members may differ in terms of their proximity to the expatriate with regard to organizational hierarchy, geographical proximity, situational context and cultural similarity. Following theories on social penetration and social attraction (Altman & Taylor, 1973; Byrne, 1971; Gudykunst & Nishida, 2001; Ibarra, 1992), this (perceived) proximity can influence the social support these organizational members are willing and able to provide to expatriates.

First, the hierarchical distance of the source may influence the value of its social support due to perceived discretion and the content of the support. On the one hand, the extent to which social support is perceived as voluntary or discretionary has been shown to increase its value (Eisenberger et al., 1997). While supervisors provide assistance on a daily basis, this can be viewed as part of their job. Expatriates may experience support from their peers less frequently but on a more voluntary basis (Ng & Sorensen, 2008). Although social support from subordinates can be as voluntary as that of peers, it may be harder to accept or may even be perceived as brown-nosing. Social support by mentors seems to be more of a hybrid, as it can be more or less formally arranged and hierarchical (e.g., from seniors, supervisors or peers). On the one hand, the type of social support provided may be influenced by the hierarchical level of the source. For instance, while each individual can provide all types of social support, some hierarchical roles (e.g., supervisor) provide better opportunities to offer certain types of support (e.g., appraisal). In sum, the hierarchical proximity of the source may thus influence the type of support provided as well as its formality.

Furthermore, organizational members in multinational organizations can differ in terms of their geographical locations, employment status and/or cultural backgrounds. The geographical distance between two organizational members influences how frequently they interact or whether contact is face-to-face or virtual (Altman & Taylor, 1973; Claus et al., 2015). Moreover, an IA is quite an experience and organizational members who have not had such experiences or are currently not on an assignment themselves may struggle to provide suitable assistance to expatriates (Johnson et al., 2003). Finally, differences in cultural norms and values may cause a (perceived) distance between individuals. A vast amount of research demonstrates that cultural factors can lead to ambiguity in communication, can inhibit relational bonding and can have implications for the provision of social support (Aycan et al., 2000; Feldman & Bolino, 1999; Gudykunst & Nishida, 2001; House et al., 2004; Peltokorpi, 2007; Sias et al., 2008).

The following sections discuss how social support by specific organizational members has been found to affect the success of IAs. As the majority of reviewed studies investigated the support provided by a specific hierarchical group of organizational members, this section discusses the results according to the same division of members. For three groups – supervisors, mentors and co-workers – the influence of their support

on the success criteria is discussed. Moreover, each section includes an overview of the moderating factors, such as the other proximity dimensions, that may have influenced the results. While each section concludes with a brief summary, the overall implications are presented in the general discussion.

4.6 Supervisor support

Social support by supervisors and its impact on the success of IAs is examined by nine studies in the current review. The majority of these studies used the construct of leader-member exchange to measure the perceived supervisor support (PSS) by the expatriate (alternatives in Kawai & Mohr, 2015; Pattie, 2007; Stroppa & Spieß, 2011; Supangco & Mayrhofer, 2014).

4.6.1 Supervisor Support and Success

Support from supervisors consistently has positive effects on the satisfaction, commitment and retention of expatriates. Four studies demonstrated how PSS contributes to the job satisfaction of expatriates (Benson & Pattie, 2009; Kawai & Mohr, 2015; Stroppa & Spieß, 2011; Supangco & Mayrhofer, 2014), whereas one study demonstrated how PSS fosters expatriates' commitment (Liu & Ipe, 2010). Furthermore, because a positive impact of PSS on expatriate retention was found in two large studies (Pattie, 2007; Pattie & Benson, 2009), a smaller study attributed its nonsignificant effect to study artefacts (Pattie et al., 2013).

Results are more ambiguous regarding the criteria of adjustment and performance. While two studies demonstrated how supervisors may assist expatriates in their adjustment process (Chen, 2010; Kawai & Mohr, 2015), no such adjustment effects were found in two other samples (Kraimer & Wayne, 2004; Kraimer et al., 2001; Supangco & Mayrhofer, 2014). Similarly, supervisor support has been found to improve expatriates' performance in four studies (Kraimer & Wayne, 2004; Kraimer et al., 2001; Pattie, 2007; Pattie & Benson, 2009), whereas three other studies found nonsignificant effects (Kawai & Mohr, 2015; Pattie et al., 2013; Stroppa & Spieß, 2011).

4.6.2 Moderating Factors

A review of the included studies suggests that their mixed findings may have been caused by at least three moderating factors. The first factor relates to the possibility that expatriates have multiple supervisors/managers. Second, the context in which the support is provided may be influential. Finally, results suggest interpersonal affectivity may play a role.

As a first moderating factor, expatriates may have multiple supervisors at different geographical locations, and these have been shown to play different supportive roles. Benson and Pattie (2009) demonstrated how assistance by local, subsidiary supervisors was essential for the adjustment and retention of expatriates. In contrast, support from supervisors in the home country primarily influenced expatriates' performance and career success. Despite these findings, limited academic attention has been paid to these differing supportive roles that supervisors fulfil. This is highlighted by two studies in the current review that leave the location of the supervisor in question completely

unmentioned (Chen, 2010; Stroppa & Spieß, 2011). On a related note, no study in the current review examined whether supporting supervisors were themselves expatriates or host country nationals (HCNs) or whether cultural differences played a role.

A second factor is the context in which supervisory support is provided, as it seems to influence the value of this support. Studies demonstrate that PSS becomes more important when the overseas role is novel or ambiguous (Kawai & Mohr, 2015). Furthermore, the effect of PSS seems stronger when it is combined with support from the (parent) organization (Liu & Ipe, 2010). Additionally, five studies demonstrate that supervisors may provide unique or substitutable resources compared to other sources of social support (Pattie & Benson, 2013; Kraimer & Wayne, 2004; Kraimer et al., 2001; Stroppa & Spieß, 2011; Supangco & Mayrhofer, 2014). Although it is difficult to draw a simple conclusion, these findings suggest that the effect of PSS on IA success relies, at least partly, on the context in terms of the overseas role and the other available resources.

The final, third moderating factor involves the measurement of constructs. Although scholars typically expect common method variance to inflate effect sizes (Podsakoff et al., 2003), the opposite occurred in the current review of PSS and expatriate performance. All studies that examined expatriates' self-rated performance found nonsignificant effects of PSS (Kawai & Mohr, 2015; Stroppa & Spieß, 2011), whereas those that used supervisor evaluations of performance found mostly positive effects (Benson & Pattie, 2013; Kraimer & Wayne, 2004; Kraimer et al., 2001; Pattie, 2007; Pattie et al., 2013). One explanation for this phenomenon is that expatriates might not be able to assess their own performance very well. However, this seems questionable, as the issue did not arise when examining the impact of POS on expatriate performance. Hence, the concept of interpersonal affectivity may offer a more likely explanation (see Lefkowitz, 2000). It suggests that expatriates who have a high-quality relationship with their supervisor will generally be more positively evaluated by that supervisor without actually performing well. This would imply that the relationship identified between supervisor support and expatriate performance may have been a design artefact.

4.6.3 Conclusion

In summary, PSS is typically associated with the success of IAs. Studies consistently demonstrate that supervisor support improves the satisfaction of expatriates, whereas they suggest a small positive influence on expatriate commitment and retention. Regarding expatriates' adjustment, studies demonstrate either positive or non-existent effects of PSS. The evidence of an effect of PSS on expatriates' performance is meagre. As our review shows, the supervisor support-success relationship seems to be contingent on moderating factors such as the proximity of the supervisor, design artefacts related to the measurement of constructs, and the available or needed resources in the IA context.

4.7 Mentoring Support

Four studies in the current review examine the influence of social support by mentors on the success of IAs. Each of these studies measured mentoring support in a different way. Bozionelos (2009) asked expatriates for the number of mentors they have had, Florkowski and Fogel (1999) surveyed whether expatriates have a mentor looking

out for their interests, Littrell (2007) examined both the number of mentors and the support they provide and Lee and Kartika (2014) specifically investigate expatriates' own mentoring behaviors.

4.7.1 Mentoring Support and Success

The few studies in the current review that investigated mentoring support show mixed results. For example, while Bozionelos (1999) showed that mentoring improved the satisfaction and retention of expatriate hospital personnel, such effects were not found in a different sample (Florkowski & Fogel, 1999). Furthermore, mentoring did not influence expatriates' commitment or their adjustment (Florkowski & Fogel, 1999). In contrast, Littrel (2007) found that mentorship could improve the satisfaction, commitment, adjustment and retention of expatriates, but this only applied to minor aspects of the mentoring process, whereas the overall relationship was weak at best. Finally, Lee and Kartika's results (2014) suggest that expatriates who take on mentoring roles themselves, adjust better to their host environment and may therefore perform better.

4.7.2 Moderating Factors

The reviewed studies put forward one factor that may have affected the results, namely the geographical proximity of the mentor and the consequences this holds for the support provided. Following Littrel (2007), it is likely that the formal assignment of a mentor does not aid expatriates, but rather the expatriate is aided by the (perceived) mentoring activities and the enhanced organizational visibility. These latter two are affected by the geographical proximity of the mentor. Littrel (2007) compared mentors in the home and host countries and found that they fulfil similar as well as different supportive roles. They provide their expatriate protégés with equal amounts of career and psychosocial assistance, whereas mentors in the host country were especially capable of providing emotional support. Due to these different roles, home and host country mentorship had distinct effects on the examined success criteria. Most strikingly, both home and host mentoring could improve the satisfaction and retention of expatriates, whereas only a host mentor stimulated expatriates' adjustment and IA completion rates (Littrel, 2007). Unfortunately, Littrel did not extend her studies to proximity in terms of employment status or cultural background, but her results do provide early evidence for the influence of geographic proximity on mentor programs.

4.7.3 Conclusion

Limited conclusions can be drawn regarding the impact of mentorship on the success of IAs, mostly due to the mixed effects and the limited number of studies in this review. Nevertheless, no strong impact of mentoring support on the success of IAs was found in any of these studies. Early work further suggests that the impact of mentoring support relies on the types of support offered and that this is influenced by the geographical location of the mentor.

4.8 Co-worker Support

Nine studies in the current review have examined the effect of perceived co-worker support on the success of IAs. However, the studies in this review often did not explicitly define the hierarchical proximity between the supporting co-worker(s) and the expatriate. While some studies investigate the support by co-workers regardless of hierarchy (e.g., Malek et al., 2015), others specifically examine support by peers (e.g., Stroppa & Spieß, 2011) or by subordinates (Harrison & Shaffer, 2005). Moreover, only two included studies define how similar the co-workers were to the expatriate in terms of their geographic location, their employment situation and/or their cultural background (Claus et al., 2015; Johnson et al., 2003)

4.8.1 Co-worker Support and Success

The studies demonstrated mixed effects of co-worker support on IA success. Regarding expatriates' job satisfaction, one study found a positive effect of co-worker support in general (Bozionelos, 2009), whereas another study investigating peer support found no effect (Stroppa & Spieß, 2011). While no study examined co-worker support in relation to the commitment of expatriates, Bozionelos (2009) found that the retention of expatriates did not improve as a consequence of co-worker support (Bozionelos, 2009). Additionally, several studies demonstrated how support from co-workers stimulates the adjustment of expatriates (Chen et al., 2011; Harrison & Shaffer, 2005; Johnson et al., 2003; Lee & Kartika, 2014), whereas other studies found no effect (Malek et al., 2015) or even negative effects (Bruning et al., 2012; Claus et al., 2015; Johnson et al., 2003). An effect of co-worker support on expatriate performance seems absent (Stroppa & Spieß, 2011), except in studies examining specifically the assistance HCN co-workers provide to expatriates. In these latter studies, the support HCNs provide consistently stimulated expatriate performance (Bader & Berg, 2013; Bruning et al., 2012; Chen et al., 2011; Harrison & Shaffer, 2005).

4.8.2 Moderating Factors

One main factor seems to consistently influence the results of the reviewed studies, namely the proximity between the supporting co-worker and the expatriate. Additionally, one study found that the personal characteristics of expatriates may influence the value of co-worker support.

Two studies of co-worker support demonstrate that geographical proximity may influence the extent to which support by co-workers is beneficial to IA success. Claus and colleagues (2015) found that expatriates who more frequently experience virtual rather than face-to-face co-worker support report lower levels of adjustment. Although not the focus of their research, this suggests that face-to-face interactions between colleagues at the same geographical location are more valuable for adjustment purposes than virtual interactions between globally dispersed colleagues. Cao and colleagues (2014) demonstrate how expatriates' professional networks in the home and host country fulfil different supportive functions and therefore differentially affect expatriate satisfaction and retention.

These conclusions align with those of Johnson and colleagues (2003), who compared the support expatriates receive from other expatriates and from HCN colleagues. The expatriate colleagues are clearly situationally (and potentially culturally) similar to the expatriate, whereas HCN colleagues are both situationally and culturally different compared to the expatriate. Johnson and colleagues (2003) found that expatriate and HCN co-workers provide similar amounts of social support but that their support differs in terms of content. Therefore, support from each group has a distinct impact on the adjustment process.

Finally, results by Stroppa & Spieß (2011) suggest that co-worker support may be more valuable to certain expatriates. They found that co-worker support only improved performance among expatriates who demonstrated high levels of personal initiative. They suggest that such expatriates accept adjustment challenges, recognize their personal mistakes and actively seek out feedback in their social interactions. This allows expatriates with high levels of personal initiative to gain more from the social support they receive.

4.8.3 Conclusion

The impact of PCS in general seems rather mixed, potentially due to the wide variety of co-workers one may have in a multinational organization. It seems that more focused research attention is needed: scholars should differentiate between support from co-worker groups that are similar in terms of their position in the hierarchy, their geographical location, their employment circumstances and/or their cultural background. Subsequently, the relationship between co-worker support and IA success may become more apparent. This is illustrated by the consistent results regarding the positive effect of HCN support on expatriate performance (e.g., Bader & Berg, 2013) or by the unique contributions of support from HCNs and from expatriates to the adjustment process (Johnson et al., 2003).

4.9 Discussion

This paper systematically reviewed literature concerning the factors that moderate the relationship between organization-based social support and the success of IAs. Three theoretical paradigms – based on stress, social capital and relational exchange – were employed by the 39 included articles. Moreover, three main moderating factors were found. First, the articles demonstrated that social support is a highly complex construct in the expatriate management literature, as its source can differ in terms of its hierarchical, geographical, situational and/or cultural proximity to the expatriate. The proximity of the source may affect the value of its support. Hierarchical proximity is most frequently specified, and studies demonstrate that organizational support is most essential, closely followed by supervisor support, which stimulates success in most cases. No clear effects of mentoring were found and, similarly, co-workers seems too broad of a category to find consistent effects. Studies furthermore showed that social support may stimulate different processes based on the geographical proximity of the source. Social support sources in the home country were consistently found to fulfil different supportive functions than their counterparts in the host country. Regarding situational and cultural

proximity, future research needs to examine how these variables influence the value of support. This may be especially helpful in untangling the mixed results regarding co-worker support. Second, in line with common belief, the impact of social support was more consistently positive for proximal success criteria such as satisfaction, commitment and adjustment, which were shown to frequently mediate the effects on the more distal criteria of retention and performance. However, certain configurations of support, such as that of HCN co-workers, contradicted this general assumption, underlining the need for future research to specify the proximity dimensions. Third, this review suggests that support is more effective depending on the characteristics of the expatriate and the assignment, examples being the expatriate's cross-cultural motivation or the level of hardship.

From a theoretical perspective, this review identified three main paradigms that complement each other, especially in light of House's taxonomy of support (1981). First, stress management theories posit that social support is necessary to facilitate international transitions by reducing the uncertainty expatriates experience. Therefore, the stress paradigm applies especially to the informational and appraisal support expatriates receive, as both reduce uncertainty by clarifying what is (to be) expected. Second, theories in the social capital paradigm view resources as means by which expatriates may achieve their goals in the new cultural and work environment. Although various types of resources may fit this perspective, the general notion of the social capital paradigm is that resources are instrumental. Finally, social exchange theories argue that only social interactions that are considered fair and discretionary would make expatriates feel a psychological obligation to reciprocate. In this sense, support needs to include emotional elements in order to fit the reciprocal process of this relational paradigm. In sum, the theoretical paradigms seem complementary, as they refer to different types of support and different processes. Future research could test to what extent sources provide specific types of support and how these stimulate the processes leading to IA success.

From a more operational perspective, the large variety of social support sources in the 39 studies showed that the construct is highly multi-dimensional during the process of expatriation. Assistance in the work context can be provided by multiple organizational units (i.e., headquarters, subsidiary or sending organization), as well as by their members, who may be more or less proximal to the expatriate in multiple dimensions. This review demonstrates that the hierarchical and geographical proximity of a support source can influence the relationship between its support and the success of IAs. However, too many studies ignored this influence and did not specify the relevant information. Regarding situational and cultural proximity, workplace interactions between individuals with different cultural backgrounds, with different past experiences and on different employment terms occur on a daily basis as expatriation, in all its variants, steadily increases (Baruch et al., 2016). Although literature suggested that such differences influence the value of social interactions (e.g., Peltokorpi, 2007; Sias et al., 2008) and early studies demonstrated some effects (e.g., Johnson et al., 2003), the expatriate management literature has not sufficiently investigated the implications yet. Scholars should more

consistently report how proximal the social support source under investigation is to the expatriate.

This review suggests that the organization is the most crucial source of support in expatriates' work environments. Due to the breadth of supportive practices (see Guzzo et al., 1994), POS was found to consistently stimulate all success criteria. Moreover, results suggested that organizational support yields unique resources for expatriates, as it accounted for significant variance in success after controlling for support from other sources (e.g., Malek et al., 2015; Cao et al., 2014; Liu & Ipe, 2010; Kraimer & Wayne, 2004; Kraimer et al., 2001). This may not come as a surprise, as POS entails unique financial resources, such as tax equalization and allowances, or instrumental and informational support, such as pre-departure preparation. Future studies can investigate to what extent these practices, or POS and its dimensions (financial, adjustment and career POS), fulfil expatriates' needs in terms of House's support types (1981). Moreover, future studies could examine what elements of organizational support can be substituted with support from other sources.

As a second point regarding POS, this review demonstrates that scholars should take into account that multiple organizational entities are perceived to share responsibility for certain types of support (cf. Aycan, 1997). Expatriates form distinct perceptions regarding the supportiveness of the parent and the subsidiary organizations, and these separate perceptions account for unique variance in IA success (Kraimer & Wayne, 2004; Kraimer et al., 2001; Liu & Ipe, 2010). HRM system theory (Bowen & Ostroff, 2004) could be used to argue that the impact of POS will be larger if expatriates feel supported by both organizations. If both organizations send a consistently supportive message, the strength of this message will be enhanced, causing expatriates to reciprocate with increased affection and effort. Future research could examine to what extent parent and subsidiary organizations can create a strong supportive climate in order to synergistically enhance success rates. Similar moderation effects have been demonstrated between work and non-work domains (Takeuchi et al., 2009) and could also be examined for the various practices, the dimensions of POS or the types of support they influence (House, 1981).

Turning to supervisor support, this review demonstrates that PSS stimulates success as well. Particularly, the extent to which high-quality relationships with supervisors are formed has been demonstrated to enhance expatriates' performance and attachment (e.g., Kawai & Mohr, 2015; Kraimer & Wayne, 2004). Here too, results suggest supervisors in the home and host country fulfil different and potentially complementary supportive functions (e.g., Benson & Pattie, 2009). Nevertheless, additional research is needed to investigate how these two supervisors provide different resources and whether dual-supervision entails synergetic effects that provide a return on investment or whether it merely causes role ambiguity.

Relatedly, results suggest that supervisory support can work in synergy with POS as well. Liu and Ipe (2010) found that expatriate commitment was at its peak when expatriates perceived support from their supervisor as well as from their parent organization. HRM system strength theory (Bowen & Ostroff, 2004) may again explain these findings, as supervisors are often seen as agents of the organization who are

responsible for the direct implementation of POS (Ng & Sorensen, 2008; Rhoades & Eisenberger, 2002). If the supportive signals of supervisors and organizations are congruent, this may enhance the supportive climate that expatriates perceive. However, a synergetic effect between only PSS and parent POS existed in Liu and Ipe's (2010) study, and not with subsidiary POS. This is peculiar, as the three support sources may be expected to contribute to the same supportive climate. Unfortunately, Liu and Ipe (2010) did not report the location of the supporting supervisor or whether it concerned expatriates' perceptions of home supervisor support in particular, which would have explained why only interactions with parent POS were found. Future studies might examine to what extent supervisors and organizations in the home and host countries contribute to the same supportive climate(s). Furthermore, as PSS and POS have unique as well as similar effects on success (see Kraimer & Wayne, 2004; Kraimer et al., 2001; Liu & Ipe, 2010), future research could examine to what extent these sources provide different and similar resources.

This review did not find conclusive results regarding the support of co-workers and mentors, but this may be attributed to the situational and cultural proximity of these sources. For example, it has been argued that HCN co-workers provide unique informational resources that stimulate the adjustment process, whereas expatriates' relationships with comparable others (i.e., expatriate co-workers) may, in particular, offer emotional resources due to their similar situational context and/or similar cultural background (Adelman, 1988; Caligiuri & Lazarova, 2002; Van Bakel et al., 2015). It has already been demonstrated that support from these specific co-worker groups has differential effects on the success of IAs (e.g., Johnson et al., 2003). Similarly, it has been suggested that the cultural proximity of mentors and their protégés influences the content and value of their interactions (Feldman & Bolino, 1999). Future studies should examine to what extent (previous) employment status and cultural proximity affect the value of supportive interactions.

Finally, this review suggests that factors other than proximity influence the effectiveness of social support in general. First, social support was found to contribute more to IA success criteria under conditions of enhanced hardship. This includes conditions characterized by local resistance (Shen & Jiang, 2015), role ambiguity (Kawai & Mohr, 2015) or political and social instability (Bader et al., 2015). Second, it seems that the effectiveness of social support may depend on the personal characteristics of expatriates, such as their cross-cultural motivation (Chen et al., 2010), the extent to which they identify with the organization (Showail et al., 2013) or their personal initiative (Stroppa & Spieß, 2011). Third, as stated above, some sources of social support have synergetic effects (Takeuchi et al., 2009; Liu & Ipe, 2010) whereas others seem to complement or even substitute for each other (Cao et al., 2014; De Paul Chism, 2014; Kraimer & Wayne, 2004; Shen & Jiang, 2015; Stroppa & Spieß, 2011). Future research should examine more broadly which factors moderate the effectiveness of social support and how they do so. Best practices might exist in terms of types and forms of support that always produce effects and that should consequently be provided on each assignment. Other supportive interventions might only provide a return on investment under certain

circumstances or may require a certain mindset of the expatriate. Such moderating factors may be especially relevant because there is no longer only one type of expatriation, given the rise of non-traditional assignments and the changing profile of expatriate managers (Baruch et al., 2016; Brookfield, 2015).

This review is subject to three main limitations. First, in its search for relevant documents this review focused on success criteria related to expatriates' effort and attachment (see Table 4.1), which means that important studies examining expatriates' job satisfaction and adjustment were thus not included. However, the purpose of this review was to illustrate what moderating factors influence the effectiveness of social support, not to provide a comprehensive overview of all processes at play. We urge scholars to consider reviewing the moderating factors affecting the relationships between social support and each success criterion separately and in more detail. Moreover, future studies could include other important outcomes of IAs such as knowledge transfer, personal development, career success and well-being.

Second, in focusing on organization-based social support, this review did not consider the assistance expatriates receive from social ties outside of the work place. Valuable social resources that members of the local community may provide to expatriates (Van Bakel et al., 2015) were thus overlooked, and future studies should investigate to what extent expatriates' interactions with non-work local ties stimulate success. More important, this review excluded the support expatriates receive from their families, which has been shown to have a major influence on IA success (e.g., Lazarova et al., 2010). Taking into account insights from the current review, future studies could examine how geographical proximity (i.e., trailing vs. non-trailing) affects the supportive resources that family members provide. Subsequently, their relative impact on IA success could be evaluated. Furthermore, scholars could extend the current framework to include success criteria from the family domain, such as spousal adjustment, work-family conflict, family well-being or even family performance.

Third, a meta-analytical approach might provide more insights regarding the influence of the moderating factors. A meta-analysis could demonstrate whether hierarchical, geographical, situational and cultural proximity actually introduce discriminant validity between support sources. Moreover, meta-analysis could test statistically whether social support actually has a stronger impact on the more proximal criteria of IA success. Furthermore, in light of the changes in the expatriate population and the rise of new forms of assignments since the last review (see Bhaskar-Shrinivas et al., 2005), a new meta-analysis could compare the effects of social support for traditional and non-traditional expatriate profiles and for different forms of assignment.

In conclusion, social support is highly multidimensional in the context of IAs and while it has positive connotations in general, its effect on the various criteria of success may not be straightforward. The rise of the term "expatriate return on investment" indicates the necessity of a more detailed investigation. Scholars should therefore team up with multinational organizations to examine what manifestations and configurations of social support reap the most benefits. This review shows that, in order to answer this question, researchers should consider at least two dimensions of proximity of the support

source: its geographical location as well as its hierarchical relation to the expatriate. Moreover, the input and interests of multiple stakeholders involved in IAs should be considered. These stakeholders include not only the organization and the expatriate but also the expatriate's family, other organizational members and members of the local community. Only by employing such a multidimensional and multi-stakeholder perspective can social support be truly instrumental for all involved.

5 Fostering expatriate success: A meta-analysis of the *differential benefits of expatriate support*

This chapter is submitted as van der Laken, P.A., van Engen, M.L., van Veldhoven, M.J.P.M., & Paauwe, J. (n.d.). Fostering expatriate success: A meta-analysis of the differential benefits of expatriate support.

Social support is recognized as an important factor for successful international assignment. However, to date, there is no overview of the agents that provide social support during the expatriation process and their influence on different criteria of expatriate success. We culminated findings of 84 independent studies that examined the social support provided by community-, work-, and family-domain agents in relation to four criteria of expatriate success: cross-cultural adjustment, commitment, performance, and retention. Our meta-analytical results demonstrated that the strength of the support-success relationship (ρ = .24 overall) depends on the supporting agent and success criterion under study. All social support, except for support by other expatriates, related positively to expatriate adjustment. Particularly overall perceptions of organizational support and supervisory support related to expatriates' commitment. Support from each domain had equally positive relationships with expatriate performance but no significant relationships existed specifically with peer support, cross-cultural training, and adjustment-oriented organizational support. Support by spouses, supervisors, and organizations was related most positively to expatriates' retention and, here, cross-cultural training and mentoring had no significant effect. We had expected that the effect of social support would differ due to the location and mobility status of agents, but such moderating effects were not found. We found support for our moderation hypothesis that social support related more strongly to proximal (i.e., adjustment, commitment) than to distal criteria (i.e., performance, retention). No evidence was found for rater effects or strong publication bias in expatriate management research.

5.1 Introduction

For multinational organizations, international assignments are crucial in building and developing global talent pools, fostering knowledge transfer, and enhancing international business strategy and opportunities (Gupta & Govindarajan, 2000; McNulty & Tharenou, 2004; Suutari & Brewster, 2003). Yet, expatriation often has less then optimal success in reaching the intended goals of organizations (BGRS, 2015, 2016) despite their significant costs ($250k to $1M in Nowak & Linder, 2016). From the employee's perspective, international assignments offer developmental opportunities and such as developing managerial and cross-cultural skills, that often are a requisite for progression to upper management (Spreitzer, McCall, & Mahoney, 1997; Stahl, Chua, Caligiuri, Cerdin, & Taniguchi, 2009; Suutari & Brewster, 2003). Nevertheless, unsuccessful expatriation may harm expatriates' personal career and well-being as well as that of their family, who have often made personal sacrifices for the assignment (Adelman, 1988; Bhaskar-Shrinivas, Harrison, Shaffer, & Luk, 2005; Black, Gregersen, & Mendenhall, 1992; Copeland & Norell, 2002; Lazarova, Westman, & Shaffer, 2010). Although the stakes are thus high during international assignment, recent surveys show that many are not successful in the eyes of organizations and employees alike (BGRS, 2015, 2016).

Fortunately, successful expatriation can be fostered by social support from the work, the family, and community domains. In the work domain, expatriates interact with multiple organizations and their members. Sending and receiving organizations implement various practices to assist, motivate, and take care of the expatriate and his/her family, including logistical services, extensive remuneration packages, and cross-cultural training (CCT; Guzzo, Noonan, & Elron, 1994). Coworkers provide tangible aid, helping with daily work tasks, assisting in the acculturation and socialization process, or directly reducing work demands (Chiaburu & Harrison, 2008). Spouses and other family members offer emotional support to the overseas work and life challenges expatriates face and provide encouragement to prevent withdrawal from the assignment. Daily interactions with friends or acquaintances in the general community members may hold emotional value and provide opportunities to learn cultural behaviors and habits (Caligiuri, 2000; Johnson, Kristof-Brown, Van Vianen, De Pater, & Klein, 2003).

Agents in different domains may offer different kinds of resources, and can therefore result in different benefits (Alcover, Rico, Turnley, & Bolino, 2017). Agents differ in terms of their cultural, hierarchical, and/or physical distance to expatriates. Cultural differences in (in)formal communication, in work behaviors, in interpersonal behaviors, and in management styles may make social interactions more difficult (Altman & Taylor, 1973; Byrne, 1971; Gudykunst & Nishada, 2001). The hierarchical nature of exchange relationships at work may put social interactions in a different light and may allow organizational agents to be more or less effective in providing specific types of social support (Raabe & Beehr, 2003). Finally, some agents are physically close to the expatriate (e.g., trailing family or local team members) whereas others reside back in the home country and can only provide support virtually. These characteristics of agents likely

affect the extent to which they can and will – formally or informally – provide information, knowledge, emotional counselling, mentoring, supervision, or task assistance.

The primary purpose of this meta-analysis is to clarify and quantify the impact of different forms of social support on expatriate success. Scholars have examined the social support of many different agents as well as multiple indicators of success. Our meta-analysis culminates these various results into an overarching understanding of the agents providing social support, their differential effects on success criteria, and the moderating influences of mobility status and physical proximity on these relationships. The next section discusses the criteria of expatriate success considered in this meta-analysis, the theoretical linkages between social support and expatriate success, and our resulting hypotheses.

5.2 Success Criteria

The success of international assignments has been studied for several decades. Traditionally, assignments were considered successful as long as the expatriate remained overseas for the proposed duration of the assignment (e.g., Tung, 1987). Following a focus on completion of assignment as a criterion, Black, Mendenhall, and Oddou's seminal paper (1991) was the start of cross-cultural adjustment as the dominant criterion of expatriate success. For a long time, adjustment, performance, and assignment completion were regarded as interchangeable measures. More recently, scholars proposed that these constructs are unique aspects of expatriate success that need to be studied separately. Moreover, scholars started to study expatriate success using more fine-grained cognitive and behavioral measures (Caliguiri, 1997; Harrison & Shaffer, 2005; Lazarova & Thomas, 2012; Thomas & Lazarova, 2006). Via meta-analysis, we can explore how these success criteria differ in terms of effect size, strength, and boundaries of their relationship with social support.

This meta-analysis sought to approach expatriate success in a broad sense and to disentangle and quantify the effects of different types of support on the various success criteria. In order to balance between psychological processes and organizational outcomes, we included both dominant proximal criteria (adjustment and commitment) as well as distal criteria (performance and retention) of success. Starting with assignment completion and expatriate retention, scholars have mostly examined expatriates' psychological withdrawal from the international assignment, from the host country/organization, or from the organization as a whole (Guzzo et al., 1994). Cross-cultural adjustment, referring to the psychological comfort that individuals experience while living abroad, has been studied in relation to the general culture, to interactions with host country nationals, and to work specifically (Black et al., 1991). Organizational commitment regards expatriates' beliefs in organizational goals and values as well as their desire to remain a member of the organization (Mowday, Porter, & Steers, 1982). Three dimensions of commitment are often considered: affective commitment, involving the emotional attachment to the organization, continuance commitment, related to the perceived costs of leaving, and normative commitment, referring to a perceived obligation to the organization (Meyer & Allen, 1991). Expatriates' performance behaviors involve many different aspects, including technical aptness (e.g., task expertise), managerial

performance (e.g., relationship management), prosocial behaviors (e.g., helping), and expatriate-specific behaviors (e.g., knowledge transfer; Caligiuri, 1997; Harrison & Shaffer, 2005). These criteria could have partially similar and partially different relationships with social support.

5.3 Social Support

Expatriates and their families face the challenge of adjusting to a new physical, cultural, and work environment. The changes in work and family roles associated with these transitions deplete an expatriate's resources (e.g., time, energy, emotions). Simultaneously, spouses and other family members experience a disruption of their established social network, often resulting in feelings of isolation, loneliness, depression, and stress (Copeland & Norrell, 2002). Under such dire circumstances, social support becomes increasingly important (Viswesvaran, Sanchez, & Fisher, 1999). Emotional, informational, and instrumental support may aid expatriates and their families in managing the international transition by replenishing their psychological resources, widening the pool of available resources, and replacing or reinforcing resources that are lacking (Halbsleben, 2006; Hobfoll, 1988).

Many different theories have been used to explain the relationship between social support and expatriate success criteria. We identified and integrated the three most dominant theoretical perspectives into a single explanatory framework (see Figure 5.1).

First, social capital and social network theories (e.g., Adler & Kwon, 2002; Lin, 1999; Seibert, Kraimer, & Liden, 2001) explain the support-success relationship from a relatively broad perspective. In general, these theories propose that valuable resources are embedded within social networks and that expatriates may access and leverage these resources when needed. The left part of Figure 5.1 represents these social networks, where a variety of supportive agents provides social resources (e.g., friendship, work advice) which expatriates may leverage to directly stimulate both proximal (e.g., adjustment; Figure 5.1, arrow 1) and distal outcomes (e.g., retention; Figure 5.1, arrow 3).

Second, anxiety and uncertainty management theories (e.g., Ashford & Taylor, 1990; Gudykunst & Nishida, 2001) provide a second, more narrow perspective on the support-success relationship. This perspective poses that the transfer to a new cultural environment brings along considerable, straining uncertainty, which may be reduced by social resources that provide information about the context or elements thereof. This theoretical perspective is not limited to specific agents, but does seem focused on informational resources – cross-cultural, normative information in specific. Anxiety/uncertainty reduction involves expatriates using these informational resources to improve their direct psychological state (e.g. adjustment; Figure 5.1, arrow 1), potentially causing positive effects on other criteria in the long-term (e.g. performance, retention; Figure 5.1, arrow 2).

A third explanation for the support-success relationship is provided by theories on social exchange (e.g., Gouldner, 1960; Kurtessis, Eisenberger, Ford, Buffardi, Stewart, & Adis, 2017; Raabe & Beehr, 2003; Rousseau, 1989; Seers, 1989). Social exchange theories state that expatriates may engage in exchanges with agents in their social environment. These exchanges influence the balance of the relationship in terms of the perceived and

psychological obligations, thereby influencing the amount of effort and affect exerted on both behalves. Social exchange theories are thus broadly applicable, in the sense that they can cover all types of social support (e.g., information, emotional, instrumental) and a variety of behaviors by the expatriate in return. For instance, social exchange theories could explain expatriates' family-oriented efforts in response to family support, or citizenship and knowledge-sharing behaviors in response to community support. However, in light of the success criteria considered in this meta-analysis, we apply the social-exchange perspective narrowly in the sense that it is limited to expatriates reciprocation in terms of commitment (Figure 5.1, arrow 1) and increased performance and retention (Figure 5.1, arrow 3) in response to the support provided by work-domain agents.

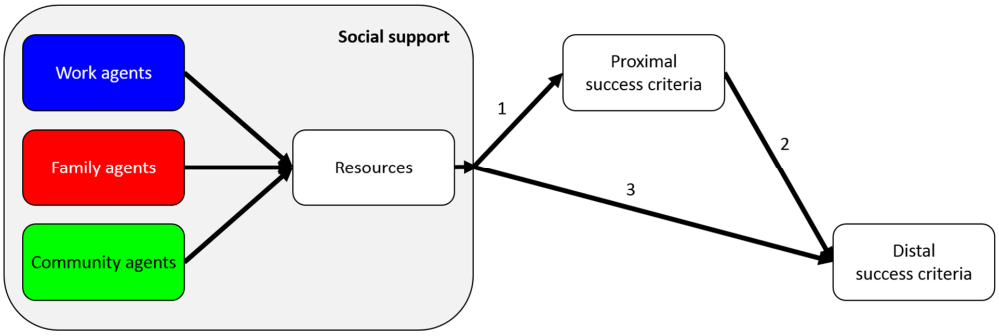

Figure 5.1: An explanatory framework of the relationship between social support and expatriate success criteria, integrating social capital, social exchange, and uncertainty management theories.

In sum, multiple theoretical perspectives explain how social support in general positively influences the success criteria under study. Hence, we expect to find overall positive relationships (Hypothesis 1). Social exchange theories emphasize the importance of social support from the work domain for commitment, retention and performance outcomes. Therefore, we expect specifically these three outcomes to be more strongly influenced by support from the work domain compared to support from the community and family domains (Hypothesis 2).

Hypothesis 1. Social support relates positively to international assignment success in terms of expatriates' (a) cross-cultural adjustment, (b) organizational commitment, (c) performance, and (d) retention.

Hypothesis 2. Social support from the work domain has a stronger influence on expatriates' (b) organizational commitment, (c) performance, and (d) retention than social support from family and community domains.

5.3.1 Agent proximity

Previous studies suggest that the value of social support can be affected by the proximity of the supporting agent (for an overview, see Chapter 4). This proximity can

refer to the cultural, physical, or hierarchical distance (or closeness) between the supporting agent and the expatriate. In this meta-analysis, we examine specifically whether the mobility status and physical proximity of supporting agents affects the value of their social support.

First, expatriates are expected to seek and attach more value to support from other expatriates than to support from host country nationals (HCNs). The similarity-attraction hypothesis (Byrne, 1971) suggests that individuals with similar attitudes, opinions, abilities, or behaviors are more strongly attracted to each other and therefore develop relationships of a higher quality. Additionally, anxiety/uncertainty management theory (Gudykunst & Nishida, 2001) proposes that interpersonal communication is more straining and less effective if agents are culturally different. Hence, while HCNs are constrained by cultural and/or language barriers, social support as provided by other expatriates will be perceived as relatively more valuable as these agents have personally experienced similar cross-cultural transitions. Earlier research demonstrates that expatriates perceive more social support from other expatriates, as compared to HCNs, and that this support is perceived as more emotionally valuable (Adelman, 1988; Johnson et al., 2003). However, the opposite may apply to adjustment outcomes. Research shows expatriates benefit more from the support received from local HCNs, whose assistance would include valuable information that allows the learning of norms, values, and appropriate behaviors in the new culture (Caliguiri, 2000; Johnson et al., 2003). In summary of the above, we expect that the social support offered by expatriates relates more strongly to commitment, performance, and retention outcomes, while social support by HCN agents is more valuable for adjustment outcomes.

Hypothesis 3. Social support by HCN agents relates more strongly to (a) cross-cultural adjustment while social support by expatriate agents relates more strongly to (b) commitment, (c) performance, and (d) retention.

Second, we expect physical proximity to influence the value of social support. Agents in an expatriate's home country network may experience difficulties being of assistance due to the physical distance: they cannot physically assist with everyday tasks, they lack cultural and situational information, and they may have trouble providing warmth or empathy. Some early evidence demonstrates such effects for work-domain support. Benson and Pattie (2009) found that home country supervisors typically "*lack the local knowledge necessary to help expatriates adjust*" while host supervisors "*understand the local culture and can provide the mentoring necessary for successful adjustment*" (p. 62). Home country supervisory support would still stimulate commitment and performance criteria as expatriates seek to validate the decision to deploy them overseas. Littrell (2007) found that support from peers and mentors in the home country was more emotionally-oriented whereas host country agents provided more adjustment-oriented support. Hence, the latter had stronger effects on expatriates' socialization, cross-cultural adjustment, and retention (Litrell, 2007). In sum, we expect social support by host country agents to have a stronger influence on expatriates' adjustment and retention whereas we expect no differences for commitment and performance outcomes.

Hypothesis 4. Social support by host country agents has a stronger influence on expatriates' (a) cross-cultural adjustment and (d) retention, as compared to social support by home country agents, whereas no differential influence exists on expatriates' (b) commitment and (c) performance.

5.3.2 Criterion proximity

As mentioned earlier, expatriate success has been measured using proximal and distal criteria. Expatriate adjustment is considered a proximal criterion as it resembles the individual process through which expatriates become comfortable in their new work and cultural environment, allowing them to focus, perform well and remain in their assignment. Cross-cultural adjustment thus is a mediating factor in the causal chain between social support and more distal criteria such as performance and retention (Harrison & Shaffer, 2005; Lazarova & Thomas, 2012; Thomas & Lazarova, 2006). Similarly, expatriates' commitment to the organization is a proximal criterion as it is an early indicator of long-term retention (Aycan, 1999) and entices expatriates to perform well in order to remain (Meyer et al., 2002; Thomas & Lazarova, 2006). Because the causal link between social support and proximal criteria is closer, the direct effects are likely stronger.

Hypothesis 5. Social support relates more strongly to proximal criteria of success (i.e. cross-cultural adjustment and commitment) than to distal criteria (i.e. performance and retention).

5.4 Methods

5.4.1 Search Strategy

In September 2015, relevant published and unpublished studies were identified in three ways. First, the databases of Web of Science, EBSCOhost[3], and ScienceDirect were systematically searched for relevant documents. Titles, abstracts and subject terms were searched for 130 keyword combinations (Table 5.1), resulting in 1098 references representing 709 unique documents. Second, we searched Web of Science and Google Scholar for studies that cited our included documents (i.e., "snowballing"), resulting in an additional 24 documents with potential for inclusion. Finally, leading scholars and journals were consulted in order to identify and collect unpublished documents. A request for studies was distributed via mailing lists and online fora[4] and recent issues of several journals[5] were manually searched for relevant documents. Because neither resulted in

[3] Business Source Elite, PsychARTICLES, PsychINFO, Psychological and Behavioral Sciences Collection were included.

[4] The Human Resources, Organizational Behavior and International Management divisions of the Academy of Management, the Academy of International Business, the SIOP, the BAM, the EURAM, the EAWOP, www.expat-research.org, and several LinkedIn groups.

[5] Academy of Management Journal, International Business Review, International Journal of Human Resource Management, Journal of Applied Psychology, Journal of Global Mobility, Journal of International Business Studies, Journal of Management, Journal of World Business, and Personnel Psychology.

new documents, we are confident that our meta-analysis is representative for the current body of research.

5.4.2 Inclusion Criteria

To be included in the meta-analysis, documents had to meet three criteria. First, only English documents were included to avoid construct ambiguity and interpretation errors. Second, their sample had to involve individuals who had recently relocated to a country other than that of their origin and for work-related reasons. Samples of missionaries, military personnel, entrepreneurs, and employees of non-governmental organizations were thus included; samples of tourists, refugees, and students were not. Third, documents had to empirically examine and report the relevant statistics on at least one relationship between social support and success criteria (i.e., adjustment, commitment, performance, or retention). Documents were excluded if the relevant statistics were not reported and the authors did not respond to or were unable to fulfill our request for such data.

The first author and a research assistant who received extensive training independently coded each document for inclusion. The complete database of 733 documents was evaluated following the step-wise process described above. Eighty-seven documents were unanimously marked for inclusion and 607 documents were unanimously rejected, resulting in an interrater reliability of 94.7%. Of the thirty-nine documents with discordant ratings, twenty were included after tripartite discussion with the second author. However, of these twenty documents, eleven authors were unable to provide the necessary statistics and two documents were the working papers of already included published papers.[6] The final set of 94 documents represented 84 independent samples.

Table 5.1: Keywords by their respective cluster.

Social support	Expatriate success	Sample
support	adjustment	expat*
	adaptation	sojourn*
	acculturation	inpat*
	performance	transpat*
	effectiveness	country national*
	success	global professional*
	failure	global worker*
	attrition	overseas assign*
	retention	international assign*
	intent*	global assign*
	cognition*	
	withdraw*	
	commit*	

Note: 130 (1 x 13 x 10) keyword combinations were used. An asterisk (*) means that the keyword was truncated and thus extended versions of that keyword were also included.

[6] An overview of included and excluded studies can be provided upon request.

5.4.3 Coding

We retrieved 852 effect sizes relating social support to success criteria, which the first author and another research assistant coded for several characteristics. Social support constructs were categorized on two levels – domains and agents – and a third level for organizational practices (family domain [spouses], community domain [HCNs, expatriates], work domain [peers, supervisors, mentors, organization]). For agents, we recorded their physical locations (home; host) and mobility status (HCN; expatriate). Additionally, for support by organizations, we distinguished between cross-cultural training, logistical support (i.e., assistance with previews, relocation, spousal employment, healthcare and education), repatriation support, and perceptions of overall organizational support and its dimensions (i.e., adjustment, career, and financial). Similarly, success criteria were categorized on two levels (adjustment [general, interaction, work], commitment [affective, normative, continuance], performance [task, extra-role], retention [in assignment, in country, in organization]). Moreover, we recorded measurement reliabilities and raters (self, spouse, supervisor, peer, hybrid, other). Several sample- and document-level characteristics were recorded as well but not reported consistently enough for analysis (e.g., sector, gender ratio, assignment duration). The estimated interrater reliability was 93.8% for the effect size characteristics, ranging between 83.3% (agent's location) and 99.8% (success criteria [level 1]), and all inconsistencies were solved in tripartite with the second author.[7]

5.4.4 Meta-analytical Procedure

Because all effect sizes were correlation coefficients, we followed Hunter and Schmidt (2004) and estimated the mean true score correlation (ρ) by correcting for measurement error. If no measurement reliability (Cronbach's α) was reported, we used the average reliability of that specific construct across all included samples. In case of reversely scored scales (e.g. family problems, turnover intentions), correlations were recoded so that a positive value indicates a positive relationship between support and success. One outlier, representing a perfect true correlation between family support and success, was found using schematic plot analysis and excluded from the final sample. Because not all correlations were statistically independent, we calculated one synthetic effect size per sample, using adjusted weighting to minimize bias in heterogeneity estimates (Cheung & Chan, 2004, 2008).

Random effects models were conducted in R (R Core Team, 2017) using the *metafor* package (Viechtbauer, 2010). Random effects allow inferences regarding participants and contexts different from those included in the samples (Field, 2001; Hedges & Vevea, 1998) and therefore more appropriate if we seek to generalize results to the global business expatriate population. However, we do note that the statistical power to test moderator hypotheses is low in random effects models (Hedges & Pigott, 2004). For each support-success relationship, we estimated the mean effect size across studies, its confidence and credibility intervals, and several heterogeneity statistics. A 95% confidence interval (CI)

[7] An example of the coding sheet can be provided upon request.

which excludes zero indicates that the population parameter is likely not zero whereas a 80% credibility interval (CR) that includes zero suggests that additional variance may be explained by moderating factors (Whitener, 1990). Higgins and Thompson's I^2 (2002) represents the proportion of the total variability in effect sizes that can be attributed to the heterogeneity of effect sizes. Cochran's Q (Cochran, 1950) was used to test the remaining heterogeneity within (Q_w) and explained heterogeneity between effect sizes (Q_b). For moderator analyses, a significant between-group homogeneity statistic (Q_b) indicates that the moderator variable explained significant variance between effect sizes whereas non-overlapping confidence intervals indicate significant differences in effect size estimates between subgroups exist at the p = .05 level (Hunter & Schmidt, 2004). Duval and Tweedie's (2000) *"trim and fill"* method was used to obtain a publication-bias-adjusted estimate of the true mean effect size. This method can be used as a sensitivity analysis, providing an indication of how the effect size could have affected by publication bias (Rothstein, Sutton, & Borenstein, 2006, p. 142). Finally, we used the estimated effect sizes to algorithmically construct a graphical mapping of the support-success relationships (see Kamada & Kawai, 1989), with stronger relationships resulting in shorter, broader edges, and constructs with similar relationships being co-located.

5.5 Results

5.5.1 Main Effects

Table 5.2 displays the overall relation found between social support and expatriate success. After pooling dependent effect sizes, the average true effect size of the 84 independent samples is estimated at ρ = .24. With significant heterogeneity remaining (Q_w = 2581.55, p < .001), we added a moderator term for the specific criteria. This improved model fit significantly (Q_b = 12.38, p < .01) and the results were in line with Hypotheses 1a through 1d with positive relationships between social support and expatriates' adjustment (ρ = .25), commitment (ρ = .33), performance (ρ = .19), and retention (ρ = .21). Examining subdimensions of criteria only improved model fit significantly for commitment outcomes (Q_b = 11.75, p < .01), where social support had no significant effect on continuance commitment. Because of the above, further analysis were conducted on each criterion separately.

5.5.1.1 Cross-cultural Adjustment

Table 5.3 displays that social support from each domain has similar positive relationships with expatriates' cross-cultural adjustment, confirming Hypothesis 2a: ρ = .25 for community support, ρ = .32 for family support, and ρ = .24 for work-related support. Within domaims, the relationship between HCN community support and adjustment remained positive (ρ = .22) but support by expatriate community members had no significant association (ρ = .13). The estimated effect of spousal support was slightly higher (ρ = .32) than family support in general (ρ = .25). Support from different coworker groups had similar effects with ρ = .27 for mentor and peer support, and ρ = .24 for supervisory support. Regarding organizational support, the relationship between adjustment and perceived adjustment-oriented support was most notable (ρ = .36).

Logistical support related positively to adjustment (ρ = .20). Repatriation support was not related to expatriate adjustment as evidenced by the confidence interval including zero.

Table 5.2: Random effects meta-analysis of social support and success criteria.

	k	*N*	*r*	ρ	se	CI95	CR80	I^2	Q_w	Q_b
Success	84	17718	.21	.24	.01	[.22, .27]	[.08, .40]	96.67%	2581.55***	
Adjustment	60	12506	.21	.25	.02	[.21, .29]	[.04, .45]	97.54%	2507.40***	12.38**
Aggregated	20	4200	.26	.31	.05	[.21, .40]	[.07, .38]	97.66%	895.98***	4.47
General	36	7420	.20	.23	.02	[.18, .27]	[.05, .42]	91.37%	426.81***	
Interaction	33	6968	.20	.23	.03	[.18, .28]	[.02, .59]	93.50%	521.26***	
Work	41	9184	.20	.22	.02	[.18, .27]	[.03, .42]	93.98%	695.87***	
Commitment	18	3549	.28	.33	.03	[.27, .40]	[.15, .52]	95.97%	515.28***	
Aggregated	7	1565	.31	.38	.04	[.30, .45]	[.15, .55]	87.51%	62.31***	11.75**
Affective	12	2077	.30	.35	.05	[.26, .44]	[-.03, .20]	95.12%	272.72***	
Continuance	3	685	.07	.09	.05	[-.02, .19]	[.06, .63]	79.54%	26.53***	
Normative	4	1009	.29	.35	.11	[.13, .57]	[.25, .51]	93.27%	62.39***	
Performance	33	5703	.16	.19	.02	[.15, .23]	[.03, .35]	89.84%	343.38***	
Extra-role	10	2083	.20	.25	.04	[.18, .32]	[.11, .40]	89.15%	105.79***	2.92
Task	31	4744	.15	.17	.02	[.12, .22]	[-.01, .35]	88.47%	277.86***	
Retention (in)	27	6167	.18	.21	.02	[.16, .25]	[.06, .35]	89.75%	271.55***	
Assignment	19	3188	.17	.20	.03	[.14, .26]	[.02, .37]	89.81%	192.31***	1.23
County	3	372	.13	.14	.08	[-.02, .30]	[-.04, .32]	91.31%	37.91***	
Organization	13	3720	.19	.21	.02	[.17, .25]	[.12, .31]	70.57%	46.15***	

Note: *k* = number of independent studies; *N* = total independent sample size; *r* = estimated correlation in the population; ρ = estimated true correlation in the population; se = standard error of the true correlation; CI95 = 95% confidence interval of the true correlation; CR80 = 80% credibility interval of the true correlation; I^2 = variance in true effect sizes as proportion of total variance; Q_w = test of within-group homogeneity; Q_b = test of between-group homogeneity.

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

Table 5.3: Random effects meta-analysis of social support and cross-cultural adjustment

	k	*N*	*r*	ρ	se	CI95	CR80	I^2	Q_w	Q_b
Community domain	9	2100	.21	.25	.07	[.12, .38]	[.00, .50]	97.05%	350.87***	4.21
General friends	5	1589	.27	.32	.10	[.11, .52]	[.02, .62]	97.18%	179.33***	2.92
Expatriates	5	795	.11	.13	.09	[-.04, .30]	[-.12, .38]	94.88%	64.23***	
Host country nationals	6	870	.19	.22	.09	[.04, .40]	[.07, .51]	95.37%	64.24***	
Family domain	19	3791	.27	.32	.03	[.26, .39]	[.13, .52]	94.79%	396.30***	
General family	9	2188	.21	.25	.11	[.03, .47]	[.17, .67]	98.23%	340.30***	0.48
Spousal support	12	1929	.26	.32	.04	[.23, .40]	[.13, .50]	94.91%	141.70***	
Work domain	49	10726	.21	.24	.02	[.19, .28]	[.04, .43]	97.16%	1768.36***	
Mentoring	7	1268	.24	.27	.12	[.03, .50]	[.14, .68]	98.60%	318.28***	9.77
Peer support	13	3235	.23	.27	.05	[.18, .36]	[.05, .49]	96.46%	185.23***	
Supervisory support	11	2257	.21	.24	.03	[.19, .30]	[.13, .36]	78.11%	37.31***	
Cross-cultural training	17	3624	.15	.16	.06	[.05, .28]	[.14, .47]	97.96%	683.03***	
Logistical support	6	1222	.17	.20	.05	[.10, .30]	[.03, .37]	90.53%	44.44***	
POS	18	3705	.20	.23	.04	[.16, .31]	[.03, .44]	92.99%	201.72***	
POS adjustment	4	727	.31	.36	.07	[.22, .49]	[.18, .53]	85.62%	27.39***	
POS career	7	1450	.20	.23	.08	[.07, .40]	[.05, .52]	94.95%	94.26***	
POS financial	9	1646	.21	.25	.05	[.16, .33]	[.07, .42]	86.90%	76.40***	
Repatriation support	5	1698	.11	.12	.07	[-.03, .26]	[-.09, .33]	89.27%	34.92***	

Note: *k* = number of independent studies; *N* = total independent sample size; *r* = estimated correlation in the population; ρ = estimated true correlation in the population; se = standard error of the true correlation; CI95 = 95% confidence interval of the true correlation; CR80 = 80% credibility interval of the true correlation; I^2 = variance in true effect sizes as proportion of total variance; Q_w = test of within-group homogeneity; Q_b = test of between-group homogeneity; POS = perceived organizational support.

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

Table 5.4: Random effects meta-analysis of social support and commitment.

	k	*N*	*r*	ρ	se	CI95	CR80	I^2	Q_w	Q_b
Community domain	3	299	.25	.30	.06	[.18, .42]	[.16, .43]	32.80%	4.48	5.23
Host country nationals	2	209	.24	.28	.12	[.05, .52]	[.06, .50]	76.03%	4.17*	23.95***
Family domain	2	428	.07	.08	.02	[.04, .12]	[.04, .12]	0.00%	0.89	
Spousal support	2	428	.07	.08	.02	[.04, .12]	[.04, .12]	0.00%	0.89	13.29***
Work domain	16	3103	.30	.35	.04	[.28, .42]	[.17, .53]	95.66%	444.15***	
Mentoring	2	351	.20	.23	.05	[.14, .33]	[.14, .32]	0.00%	0.83	71.50***
Peer support	2	888	.20	.25	.04	[.18, .32]	[.18, .32]	7.46%	1.08	
Supervisory support	3	482	.32	.36	.07	[.22, .50]	[.20, .52]	66.44%	6.42*	
Cross-cultural training	5	718	.13	.16	.04	[.08, .24]	[.04, .28]	63.62%	11.50*	
Logistical support	4	615	.18	.22	.04	[.13, .30]	[.11, .33]	20.91%	4.87	
POS	9	2056	.44	.52	.04	[.43, .60]	[.34, .69]	92.65%	60.95***	
POS adjustment	2	348	.24	.28	.13	[.02, .53]	[.04, .51]	86.68%	7.51**	
POS career	5	876	.28	.32	.06	[.20, .43]	[.15, .49]	83.40%	39.74***	
POS financial	7	1197	.23	.27	.06	[.15, .39]	[.06, .47]	90.26%	44.97***	
Repatriation support	3	605	.15	.18	.05	[.08, .28]	[.07, .29]	76.85%	10.52**	

Note: k = number of independent studies; *N* = total independent sample size; *r* = estimated correlation in the population; ρ = estimated true correlation in the population; se = standard error of the true correlation; CI95 = 95% confidence interval of the true correlation; CR80 = 80% credibility interval of the true correlation; I^2 = variance in true effect sizes as proportion of total variance; Q_w = test of within-group homogeneity; Q_b = test of between-group homogeneity; POS = perceived organizational support.

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

5.5.1.2 Commitment

Table 5.4 demonstrates positive relationships between support from each domain and expatriates' commitment. The results are not fully in line with Hypothesis 2b, as work-domain support displayed a stronger effect (ρ = .35) compared to the family domain (ρ = .08), but not compared to the community domain (ρ = .30). Results on the more detailed actor/type level demonstrates expatriates' commitment was most strongly related to their overall perceptions of organizational support (POS) (ρ = .52). Moreover, supervisory support related more positively to commitment (ρ = .36) than support by peers (ρ = .25) or mentors (ρ = .23).

5.5.1.3 Performance

Table 5.5 demonstrates positive relationships between social support from each domain and expatriates' performance, with ρ = .18 for community, ρ = .19 for family, and ρ = .21 for work domain support. These results are not in line with Hypothesis 2c which expected a stronger relationship with work-domain support. More detailed results within domains demonstrate that supervisory (ρ = .26) and mentor support (ρ = .19) associated significantly with high performance, but peer support did not (ρ = .17). However, the broad credibility interval and high heterogeneity statistic suggest that moderation may exist. Regarding the types of organization support, particularly logistical support and POS (both ρ = .24) related positively to performance whereas nonsignificant associations were found for cross-cultural training (ρ = .06) and adjustment-oriented POS (ρ = .08).

Table 5.5: Random effects meta-analysis of social support and performance

	k	*N*	*r*	ρ	se	CI95	CR80	I^2	Q_w	Q_b
Community domain	5	866	.15	.18	.06	[.06, .31]	[.00, .37]	72.54%	18.43**	0.25
General community	2	422	.20	.22	.18	[-.13, .58]	[-.10, .55]	93.43%	15.23***	0.02
Host country nationals	2	275	.16	.20	.06	[.09, .31]	[.09, .30]	0.00%	0.20	
Family domain	8	1335	.17	.19	.05	[.10, .28]	[.02, .35]	79.16%	41.96***	
General family	3	606	.19	.22	.09	[.03, .40]	[.01, .42]	82.54%	11.27**	0.28
Spousal support	5	729	.15	.17	.07	[.04, .31]	[.03, .38]	87.34%	25.73***	
Work domain	28	5045	.18	.21	.03	[.16, .26]	[.03, .40]	92.28%	387.14***	
Mentoring	2	381	.18	.19	.06	[.07, .30]	[.08, .29]	19.33%	1.24	9.45
Peer support	5	1376	.13	.17	.10	[-.03, .36]	[-.12, .45]	97.01%	73.89***	
Supervisory support	7	920	.23	.26	.05	[.17, .36]	[.10, .43]	66.46%	17.41**	
Cross-cultural training	4	435	.05	.06	.09	[-.10, .23]	[-.16, .28]	70.43%	10.68*	
Logistical support	2	170	.21	.24	.06	[.13, .36]	[.14, .35]	0.00%	0.38	
POS	14	3159	.20	.24	.07	[.11, .37]	[-.08, .56]	95.85%	212.18***	
POS adjustment	3	482	.06	.08	.06	[.04, .19]	[-.06, .21]	70.32%	6.68*	
POS career	4	582	.15	.18	.04	[.11, .25]	[.08, .27]	37.93%	4.90	
POS financial	4	656	.11	.13	.03	[.08, .19]	[.06, .21]	0.00%	1.78	

Note: k = number of independent studies; *N* = total independent sample size; *r* = estimated correlation in the population; ρ = estimated true correlation in the population; se = standard error of the true correlation; CI95 = 95% confidence interval of the true correlation; CR80 = 80% credibility interval of the true correlation; I^2 = variance in true effect sizes as proportion of total variance; Q_w = test of within-group homogeneity; Q_b = test of between-group homogeneity; POS = perceived organizational support.

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

5.5.1.4 Retention

Table 5.6 displays positive meta-analytical estimates of associations between expatriate retention and social support from the family (ρ = .25) and work domain (ρ = .19), in line with Hypothesis 2d. Too few studies had examined community support in relation to retention. Similarly, we could only compare different actors/types of social support within the work domain. Support by supervisors (ρ = .26) and peers (ρ = .17) related significantly to expatriates' retention, but mentoring had no significant association with retention. Career POS had the strongest association with retention (ρ = .28), followed by overall POS (ρ = .26), and financial POS (ρ = .19). Logistical support did not relate to retention but the credibility interval and the heterogeneity statistic suggested moderating effects of third variables. Cross-cultural training had a near zero correlation to retention.

5.5.2 Moderator Analyses

5.5.2.1 Agent Proximity

Table 5.7 demonstrates that mobility status did not explain significant variance in the relationship between social support and expatriate adjustment. Nevertheless, the average effect of social support was considerably higher when social support was provided by HCNs (ρ = .25), rather than by expatriates (ρ = .13), which suggests that hypothesis 3a may be confirmed when more studies would be available. Hypotheses 3b through 3d could not be tested because too few studies had specified the mobility status of agents.

Table 5.6: Random effects meta-analysis of social support and retention.

	k	*N*	*r*	ρ	se	CI95	CR80	I^2	Q_w	Q_b
Family domain	5	818	.23	.25	.03	[.19, .32]	[.16, .35]	68.84%	18.45**	0.86
Spousal support	5	818	.23	.25	.04	[.18, .33]	[.14, .36]	77.05%	18.45**	57.58***
Work domain	24	5665	.17	.19	.03	[.14, .25]	[.03, .36]	91.10%	281.21***	
Mentoring	5	898	.05	.06	.04	[-.03, .14]	[-.06, .17]	72.07%	15.12**	19.02**
Peer support	4	997	.14	.17	.02	[.13, .21]	[.11, .22]	0.16%	2.75	
Supervisory support	5	1085	.23	.26	.03	[.20, .31]	[.18, .33]	0.00%	2.51	
Cross-cultural training	3	437	.02	.03	.13	[-.23, .29]	[-.27, .32]	86.94%	16.30***	
Logistical support	4	648	.18	.20	.15	[-.09, .49]	[-.17, .57]	93.58%	46.88***	
POS	9	3076	.23	.26	.04	[.18, .34]	[.11, .42]	85.82%	68.11***	
POS career	4	593	.26	.28	.08	[.12, .45]	[.07, .50]	87.69%	27.33***	
POS financial	6	1329	.16	.19	.06	[.08, .29]	[.01, .36]	74.98%	19.64**	

Note: k = number of independent studies; *N* = total independent sample size; *r* = estimated correlation in the population; ρ = estimated true correlation in the population; se = standard error of the true correlation; CI95 = 95% confidence interval of the true correlation; CR80 = 80% credibility interval of the true correlation; I^2 = variance in true effect sizes as proportion of total variance; Q_w = test of within-group homogeneity; Q_b = test of between-group homogeneity; POS = perceived organizational support.

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

Table 5.7: Random effects models of moderator effect of mobility status

	k	*N*	*r*	ρ	se	CI95	CR80	I^2	Q_w	Q_b
Mobility status										
Adjustment										
Expatriate agent	6	991	.11	.13	.06	[.02, .25]	[-.04, .31]	90.22%	66.11***	2.41
HCN agent	19	3675	.22	.25	.04	[.18, .32]	[.04, .46]	95.73%	466.51***	
Physical proximity										
Adjustment										
Home country agent	32	7302	.18	.21	.03	[.14, .27]	[.04, .45]	97.54%	1370.11***	2.35
Host country agent	42	8387	.23	.27	.02	[.22, .31]	[.07, .46]	96.52%	1255.39***	
Commitment										
Home country agent	7	1130	.24	.28	.03	[.21, .35]	[.17, .40]	88.58%	101.58***	0.01
Host country agent	10	2171	.25	.29	.05	[.20, .39]	[.09, .50]	92.85%	152.66***	
Performance										
Home country agent	14	2078	.17	.19	.03	[.12, .25]	[.03, .35]	74.69%	57.91***	0.10
Host country agent	26	4875	.15	.17	.02	[.13, .22]	[.04, .31]	82.95%	158.91***	
Retention										
Home country agent	12	3330	.15	.16	.05	[.07, .25]	[-.04, .37]	90.79%	141.72***	0.95
Host country agent	16	2927	.18	.20	.02	[.16, .24]	[.10, .31]	72.64%	60.20***	

Note: k = number of independent studies; *N* = total independent sample size; *r* = estimated correlation in the population; ρ = estimated true correlation in the population; se = standard error of the true correlation; CI95 = 95% confidence interval of the true correlation; CR80 = 80% credibility interval of the true correlation; I^2 = variance in true effect sizes as proportion of total variance; Q_w = test of within-group homogeneity; Q_b = test of between-group homogeneity; POS = perceived organizational support.

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

Table 5.7 also demonstrates that the physical proximity of agents did not explain significant variance. Similarly, the average association between adjustment and social support was higher when agents resided in the host country (ρ = .27) rather than in the home country (ρ = .21), but this difference was not significant. The confidence intervals of the effects of social support by host and home country agents on commitment, performance and retention outcomes strongly overlapped, leading us to reject hypotheses 4a through 4d.

5.5.2.2 Criterion Proximity

Hypothesis 5 expected that studies would report a stronger relationship between social support and expatriate success when they had measured the latter with proximal (i.e., cross-cultural adjustment and commitment) rather than distal criteria (i.e., performance and retention). Table 5.8 confirmed this hypothesis with a significantly larger association between social support and proximal criteria (ρ =.27) compared to distal criteria (ρ =.19; Q_b = 8.21, p < .01).

Table 5.8: Random effects models of moderator effect of outcome criterion

	k	*N*	*r*	ρ	se	CI95	CR80	I^2	Q_w	Q_b
Proximal criteria	67	13570	.23	.27	.02	[.23, .31]	[.08, .46]	97.53%	2791.55***	8.21**
Distal criteria	51	10622	.17	.19	.02	[.16, .23]	[.05, .34]	90.79%	567.54***	

Note: k = number of independent studies; *N* = total independent sample size; *r* = estimated correlation in the population; ρ = estimated true correlation in the population; se = standard error of the true correlation; CI95 = 95% confidence interval of the true correlation; CR80 = 80% credibility interval of the true correlation; I^2 = variance in true effect sizes as proportion of total variance; Q_w = test of within-group homogeneity; Q_b = test of between-group homogeneity.

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

5.5.2.3 Rater Effects

The use of self-evaluations of performance is the norm in expatriate management literature but our results in Table 5.9 demonstrate this has not inflated the association between social support and performance outcomes. Research designs where the same respondent rates multiple variables can introduce artefactual covariance between these variables, as respondents follow response tendencies based on their personal dispositions, their beliefs regarding specific correlations, and their desires to be consistent, lenient, and compliant with social norms (Podsakoff et al., 2003). However, studies did not report significantly stronger associations when they used expatriates' self-evaluations (ρ = .19) instead of performance ratings by supervisors or peers (ρ = .19).

Table 5.9: Random effects models of moderator effect of raters

	k	*N*	*r*	ρ	se	CI95	CR80	I^2	Q_w	Q_b
Performance										
Same rater	22	3596	.16	.19	.03	[.13, .26]	[.00, .39]	91.61%	278.89***	0.03
Different rater	15	2537	.16	.19	.02	[.14, .23]	[.08, .30]	74.80%	66.93***	

Note: k = number of independent studies; *N* = total independent sample size; *r* = estimated correlation in the population; ρ = estimated true correlation in the population; se = standard error of the true correlation; CI95 = 95% confidence interval of the true correlation; CR80 = 80% credibility interval of the true correlation; I^2 = variance in true effect sizes as proportion of total variance; Q_w = test of within-group homogeneity; Q_b = test of between-group homogeneity.

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

5.5.2.4 Publication Bias

Using the *"trim and fill"* method (Duval & Tweedie, 2000), we estimated, per criterion, the number of missing studies due to publication bias. Typically, studies with small samples or nonsignificant results do not meet the requirements for publication. This causes "*research that appears in the published literature [to be] systematically unrepresentative of the population of completed studies*" (Rothstein, Sutton, & Borenstein, 2006, p. 1). We estimated the average true effect sizes before and after correcting for potential bias. Table 5.10 and Figure 5.2 suggested minor publication bias. For retention, an estimated five effect sizes were missing which would have decreased the true effect slightly, from ρ = .21 to ρ = .17. For performance outcomes, six studies with larger effect sizes were estimated missing and correcting for these increased the estimated true effect from ρ = .19 to ρ = .22.

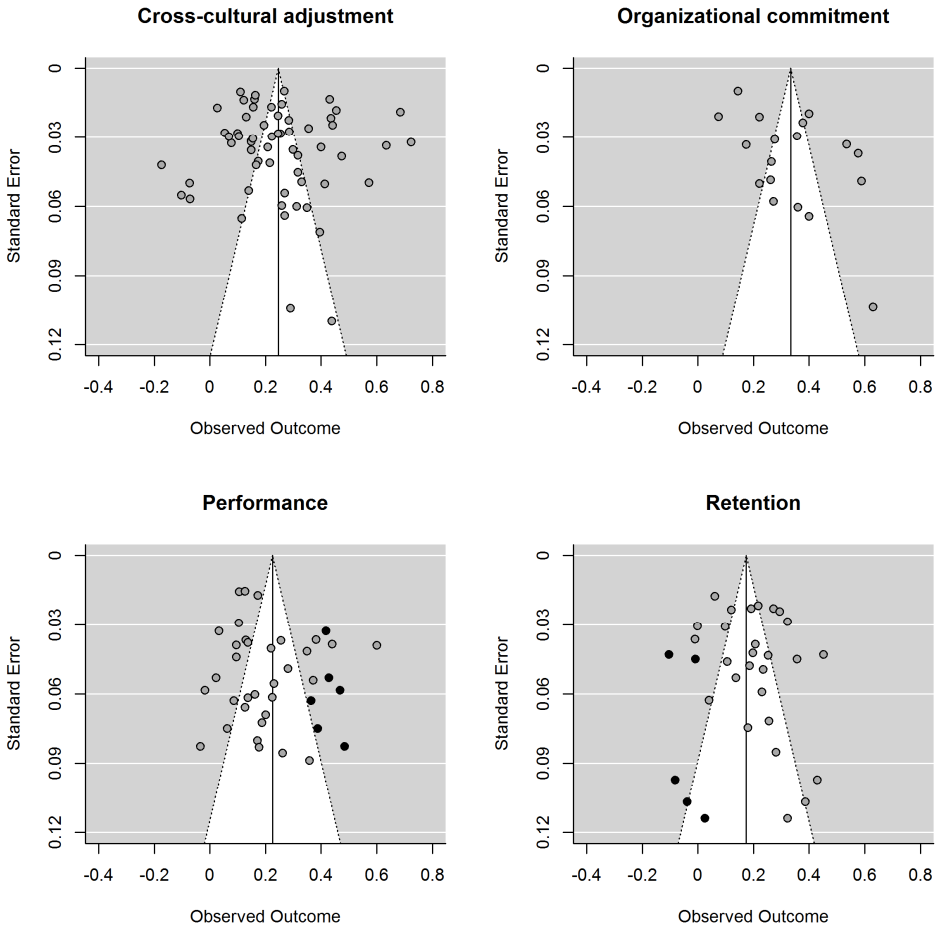

Figure 5.2. Funnel plots of the estimated extent of publication bias in literature. Grey dots represent the observed data points; black dots are estimated missing effect sizes.

Table 5.11: Random effects models estimating correction for publication bias

	Before correction						After correction				
	k	***N***	***r***	**ρ**	**se**	**CI95**	***k′***	***r***	**ρ**	**se**	**CI95**
Adjustment	60	12506	.21	.25	.02	[.21, .29]	60	.21	.25	.02	[.21, .29]
Commitment	18	3549	.28	.33	.03	[.27, .40]	18	.28	.33	.03	[.27, .40]
Performance	33	5703	.16	.19	.02	[.15, .23]	39	.19	.22	.02	[.18, .27]
Retention	27	6167	.18	.21	.02	[.16, .25]	32	.16	.17	.02	[.13, .22]

Note: k = number of independent studies; *N* = total independent sample size; *r* = estimated correlation in the population; ρ = estimated true correlation in the population; se = standard error of the true correlation; CI95 = 95% confidence interval of the true correlation; *k′* = estimated number of independent studies after including estimated missing studies.

5.5.3 Results Summary

Figure 5.3 and Table 5.11 summarize the results regarding the direct effects found in Tables 5.2 through 5.6. The network in Figure 5.3 was generated with Kamada and Kawai's (1989) graph drawing algorithm. This algorithm seeks to minimize the total length of its edges (i.e., relationships) by cleverly placing nodes (i.e., constructs). Moreover, edges were weighted for the inverse effect sizes reported in Table 5.11, so that stronger relationships were resembled by shorter, broader edges. All this implies that, in Figure 5.3, social support constructs were located closer to success criteria they related to more strongly (and vice versa), and that social support constructs and success criteria that have similar relationships were automatically co-located.

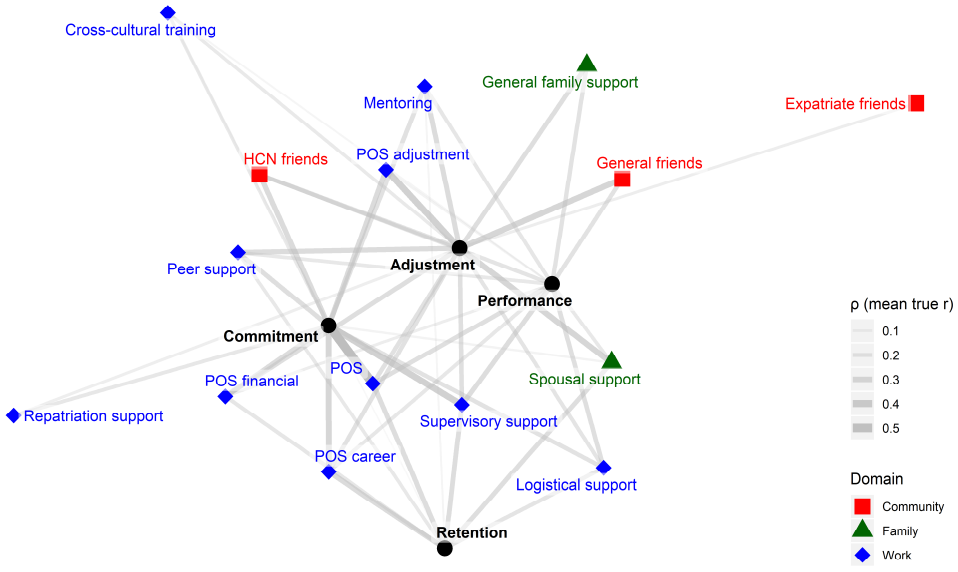

Figure 5.3. The agents/types of social support and their direct relationships to the success criteria as reported in Table 5.11, colored for their domain. No arrow indicates *k* < 2.

Table 5.11: Estimated true correlations for direct effects.

	Success	Adjustment	Commitment	Performance	Retention
Social support	.24	.25	.33	.19	.21
Community domain		.25	.30	.18	
General friends		.32		~~.22~~	
Expatriates		~~.13~~			
Host country nationals		.22	.28	.20	
Family domain		.32	.08	.19	.25
General family		.25		.22	
Spousal support		.32	.08	.17	.25
Work domain		.24	.35	.21	.19
Mentoring		.27	.23	.19	~~.06~~
Peer support		.27	.25	~~.17~~	.17
Supervisory support		.24	.36	.26	.26
Cross-cultural training		.16	.16	~~.06~~	~~.03~~
Logistical support		.20	.22	.24	~~.20~~
POS		.23	.52	.24	.26
POS adjustment		.36	.28	~~.08~~	
POS career		.23	.32	.18	.28
POS financial		.25	.27	.13	.19
Repatriation support		~~.12~~	.18		

Note: Numbers displayed are the estimated corrected true effect sizes (ρ) of the random effects models displayed in Tables 5.2 through 5.6. They vary in sample sizes, standard errors, and confidence intervals. Nonsignificant effects (95% CI includes zero) are in strikethrough whereas no effect size indicates a lack of independent samples ($k < 2$). POS = perceived organizational support.

5.6 Discussion

The primary purpose of this meta-analysis was to clarify and quantify the impact of social support on the success of international assignments of expatriates. Using data of 84 independent samples containing nearly 18,000 international assignments, we meta-analytically estimated the relationships between the social support provided from community, family, and work agents and four common criteria of expatriate success: cross-cultural adjustment, organizational commitment, performance, and retention. We validated the overall positive relationship between social support and these success criteria (Hypothesis 1). In spite of our expectations based on social exchange theories, we did not find stronger work-domain-specific reciprocation effects (Hypothesis 2). Rather, our results revealed strong crossover and spillover effects from family support on performance and retention, and from community support on performance and commitment. We also did not find moderating effects of mobility status – where we had expected that the effects of support by host country national agents and expatriate agents would differ (Hypothesis 3) – or of physical proximity – where we had expected that the support by host country agents would be stronger related to success (Hypothesis 4). Nevertheless, support by agents in the host country or agents with host country nationalities demonstrated considerable stronger associations with adjustment outcomes in our sampled studies. We confirmed that the effects of social support are stronger on proximal success criteria (adjustment and commitment) than on distal criteria (performance and retention; Hypothesis 5). Finally, we found that the relationship between social support and success was relatively robust to rater effects and publication bias.

Table 5.11 and Figure 5.3 summarize the relative impact of different supportive agents. While some agents influenced all success criteria strongly (e.g., supervisors and organizations), others stimulated specific criteria in particular (e.g., spouses and adjustment and retention). In contrast, other social support had weak effects altogether (e.g., cross-cultural training) or had yet to be examined in relation to specific criteria (e.g., expatriate friends and performance, commitment, and retention). Taken together, our results display how different agents in expatriates' social support network contribute differently to expatriate success. In the following section, we first discuss most important agents (i.e., organizations, supervisors, spouses) and specific avenues for future research, after which we turn to general implications for (future) research and practice.

5.6.1 Organizational Support

Organizational support was of primary importance to all four criteria of expatriate success considered in this study. Figure 5.3 intuitively reflects this, with all forms of social support from the work-domain encircling the four success criteria and including several broad edges. Particularly expatriates' commitment to their assignment relied considerably on their overall perception of organizational support – on whether he/she felt valued, listened to, and cared about by the organization. In relation to the other criteria, two remarkable relationship arose in relation to expatriates' perceptions regarding specific bundles – or systems – of organizational practices. First, in line with its purpose, organizational involvement in adjustment processes related strongly to the cross-cultural adjustment expatriates reported. Here, the perceived bundle of adjustment-oriented practices seems more important than its individual parts, as the effects of, for instance, cross-cultural training and logistical support were significantly less substantial. Second, expatriates' retention in the assignment was strongly related to the experienced career-oriented organizational support. Expatriation often requires personal sacrifices and, apparently, expatriates will only endure the associated challenges when their future career is looked after by the organization. Organizational support in terms of compensation and finances influenced all four criteria, but not a single one in particular.

Although these results underline the criticality of perceived organizational support to assignment success, there are at least two areas that need elaboration. First, studies should assess the contribution of individual global mobility practices and how these practices interrelate. Practices such as cross-cultural training could only be effective when bundled with, for instance, an in-country socialization to apply these newly acquired cross-cultural skills. Second, in light of the dual psychological contract expatriates have with their parent and subsidiary organizations (Gregersen & Black, 1992), it would be interesting to examine what types of support and which specific practices expatriates expect from each organization respectively.

5.6.2 Supervisor Support

Supervisory support was another salient antecedent of expatriate success that lies in the work domain. Its strong relationship to expatriates' adjustment, commitment, performance, and retention suggests that establishing high-quality leader-member relations should a top priority of sending and hosting organizations. On the one hand,

supervisors provide social resources that are unique to their supervisory role (e.g., feedback and task supervision). Such resources can aid expatriates directly in adjusting and performing in their jobs whereas they may instigate indirect cycles of reciprocity, leading to improved commitment, performance, and retention during and after assignments. On the other hand, supervisory support may also contribute to international assignment success indirectly through its effect on employees' overall perceptions of organizational support (Kurtessis et al., 2017). Supervisors are in an excellent position to provide valuable social resources, such as career guidance, that reinforce perceptions of organizational support.

Future research could explore whether synergies exist. For example, expatriates who perceive assistance from both their supervisors, their organizations, and/or their mentors may respond more strongly. Following our moderation analysis, scholars could also explore whether the similarity between supervisors and their expatriate reports affects the value of their support. Potentially effective leader-membership exchanges are inhibited by cultural barriers, as the preferred communication styles may differ across cultures, or by physical barriers, as long-distance virtual communication may demand a different leadership style.

5.6.3 Spousal Support

Finally, our results highlight the criticality of the family in the expatriation process, particularly the spouse. Spousal support improved expatriates' adjustment considerably and this is likely a result of crossover effects, where the attitudes and behaviors of an expatriate are influenced by those of another individual, or vice versa (Takeuchi, Yun, & Tesluk, 2002). Family members often experience trouble adjusting, having sacrificed their personal social network and, possibly, their career (Cole & Nesbeth, 2012; McNulty, 2012; Shaffer, Harrison, Gilley, & Luk, 2001). The negative effects of this may crossover to the expatriate, affecting his/her adjustment (Caliguiri, Hyland, Joshi, & Bross, 1998; Shaffer & Harrison, 1998; Takeuchi, Yun, & Tesluk, 2002). Moreover, spillover effects – where an expatriate's experiences in one domain influence an outcome in another domain (Takeuchi, Yun, & Tesluk, 2002) – also occurred in relation to family support. For instance, we found a strong association between spousal support and the retention of expatriates, suggesting that whether international assignments are completed is often a family decision.

Additional spillover occurred in relation to performance. Based on social exchange theory, we had expected that performance at work would primarily be influenced by the social support expatriates received from within the work domain. However, expatriates who felt supported by their family seemed to better focus their time and effort on the job, enabling them to excel in their assignments. The substantial effects estimated in this meta-analysis indicated that family support, particularly by the spouse, is an equally important antecedent for expatriates' work performance as the daily assistance provided by peers and mentors. This is highlighted by the location of spousal support in Figure 5.3, among the work-domain support constructs and relatively close to the success criteria. In sum, researchers and practitioners should not neglect the perceptions and attitudes of the expatriate family when examining expatriate success.

We propose three directions for future research on family support. First, it would be interesting to examine how the importance of supportive relations between family members changes over time. Family members are likely the main support providers during the early stages of the expatriation cycle. Expatriates strongly rely on their family members for cultural sense-making, emotional counselling, and arranging administration and accommodation, especially when their external support network is still disrupted due to the relocation. Second, family support may have increased importance during non-standard assignments. For example, assignments with elevated hardship (e.g., remote locations or terrorism-endangered countries) place higher demands on expatriate families. Similarly, the rising use of frequent commuting, rotations, and split-family arrangements (BGRS, 2016) causes completely new challenges for expatriate families as they are separated for longer periods of time. We have limited knowledge of what these developments imply for expatriates' need for support. Third, not all expatriates have a trailing family or family members to rely on at all. It would be interesting to compare the instrumentality of support from trailing and non-trailing family members. Moreover, scholars could explore to what extent the lack of a family increases expatriates' reliance on other sources of social support.

5.6.4 Research Implications & Agenda

We call for a more granular examination of social support in future expatriate management research. This study established that different agents provide different benefits, potentially at different phases of the expatriation cycle. Scholars and practitioners should be able to build on these potentially different roles and responsibilities of agents. In order to advance our theoretical understanding, we urge future studies to provide a more detailed specification of the agents and/or the support they examine, rather than referring to general social "*support*" (Black, 1990; Black & Gregersen, 1991; Tsang, 2001; Wang, 2003; Wiese, 2013), social "*networks*" (Claus, Maletz, Casoinic, & Pierson, 2015), or social "*contact*" and "*interactions*" (Jun, Lee, & Gentry, 1997; Stierle, Van Dick, & Wagner, 2002). Based on the current sample of studies, our meta-analysis puts forward several areas that require empirical elaboration.

First, there are nearly no studies that examine the effects of specific practices on expatriates' performance and retention. We urge future scholars to examine more rigorously how the global mobility practices implemented by organizations are perceived by expatriates, whether they fulfill elements of the psychological contract, and whether they help motivate and retain expatriates. Studies could compare organizations with similar policies and practices, operating in similar industries and countries, and compare retention rates.

Second, more research is required on mentorship and buddy programs during international assignment. We did establish that mentoring benefits expatriates' adjustment, commitment, and performance, but, intriguingly, not on expatriates' retention. This while mentoring seems oriented at the long-term (career) development of the protégé. Scholars have claimed that home and host mentorship have different purposes, respectively repatriate retention and expatriate adjustment (Feldman & Bolino,

1999; Littrell, 2007), but it is unclear to what extent each fulfills its purpose based on our current results.

Third, the relationship between expatriates and their subordinates seems completely neglected in contemporary literature. A large part of international assignments occurs in order to fill managerial positions abroad (30%; BGRS, 2016) and we propose that expatriates may receive assistance and information from their overseas subordinates similar to that received from any other organizational agent. Subordinates' assistance may, for instance, be helpful in learning cultural norms and adjusting to management responsibilities in a cross-cultural setting. However, neither the type of support offered by subordinates nor their overall willingness to support expatriate managers has been examined as of yet.

Fourth, it is worth considering how agents and types of social support may act as substitutes or complements. Future research could examine more closely what type of resources are provided by different agents (e.g., emotional, informational, or instrumental). Some agents may be able to provide more or less unique resources, such as the feedback of supervisors or the affection of spouses, allowing them to fulfill roles that are critical to the assignment success. Other social support can be offered by various agents, if not simultaneously, hereby causing substitution or complementary effects. Career support or task assistance can for instance be offered by supervisors, mentors, and peers, and anyone in an expatriate's social network may offer friendship or general information. Although our data format did not allow the testing of such hypotheses, future research should seek to examine the unique, substitutional, and complementary effects of social resources and their relative importance to expatriates. Such insights could be quite valuable in designing adjustment and socialization programs that optimize the international assignment experience. A first step would be to establish to what extent different agents provide emotional, informational, and instrumental resources.

Fifth, in an increasingly globally connected world, the ways in which expatriates seek and receive social support may change rapidly. Virtual means of interactions negate physical distance and international travel becomes easier and cheaper by the year. Future research on social support should examine to what extent technological developments change the way in which expatriates gather and maintain their social resources. Although digital communication and cooperation programs, such as live video feeds and cloud services, facilitate global operations, the social interactions they imply are of a different, potentially less emotional nature. Nevertheless, these communication channels are becoming a larger part of day-to-day jobs. Simultaneously, expatriates experience less daily support in non-work domains because of the shift towards more global commuting, frequent business travelling, and split-family arrangements (BGRS, 2016). Research should examine to what extent family ties suffer from such assignments and whether expatriates experience social support from peers when working in virtual teams and on the cloud.

Sixth, previous meta-analyses found that social support in domestic settings correlates .00 to .30 with performance, .20 to .70 with commitment, and -.20 to -.50 with turnover and withdrawal respectively (Chiaburu & Harrison, 2008; Kurtessis et al., 2017;

Meyer, Stanley, Herscovitch, & Topolnytsky, 2002; Riggle, Edmonson, & Hansen, 2009). Because the stressful conditions of international assignment would enhance employees' reliance on social support (Viswesvaran et al., 1999), we had expected to find relationships equal to or stronger than those in domestic settings. Indeed, the impact of social support on performance reached the upper bound of what has been found in domestic contexts (e.g., Chiaburu & Harrison, 2008), but effects on commitment and retention were lower than expected. We set out to account for the actual hardship experienced in the different samples, but this was not documented adequately in the majority of studies. Future research should examine to what extent hardship is actually experienced in different international assignment contexts, and how hardship affects the value of social support. We expect that expatriates' may have a higher need for informational, emotional, and instrumental resources during, for instance, split-family arrangements, commuting schemes, offshore postings, in terrorism-endangered countries, or under conditions of extreme cultural differences.

5.6.5 Practical Implications

Several implications for practice emerge from our meta-analysis. First of all, our meta-analysis demonstrates that organizations should focus on providing the right career opportunities to counter the issue of international talent retention. Long-term career and succession planning for expatriates is put forward as most influential of expatriates' commitment and retention in our results, yet scholars suggest that organizations put too little effort into specifically these elements (Kraimer, Shaffer, & Bolino, 2009; Lazarova & Cerdin, 2007; Pattie, White, & Tansky, 2010). The recent rise of strategic workforce planning tools (Angrave et al., 2016; Davenport, Harris, & Shapiro, 2010) should allow organizations to plan ahead and make sure a new assignment or a home position that fits the developed capabilities is available for repatriates.

Second, our findings underline the crucial support function family members fulfill during expatriation. Organizations are wise to be generous in supporting families and spouses in the overseas adjustment process. However, frequent business travelling, overseas commuters, and split family arrangements are becoming ever more common because of the cost-savings they imply on the short term (BGRS, 2015, 2016; McNulty, 2015). These cost-efficiencies could have negative implications in the long term. They may seriously damage expatriates' support networks, causing decreases in well-being and the rise of work-family interferences that harm both the assignee and the assignment. With time, this could result in decreased productivity, long-term absence, and dysfunctional turnover. Hence, organizations turning to these alternative means of expatriation should take their social responsibility and facilitate ongoing, honest discussion with expatriates regarding their families' well-being and work-life balance.

Finally, although cross-cultural training and social club memberships remain standard practice in most organizations (BGRS, 2015; Cole & Nesbeth, 2014), our results suggest they are inefficient. CCT only related to small improvements in expatriates' commitment and adjustment, in line with a previous meta-analysis (Morris & Robie, 2001), but did not improve behavioral outcomes such as performance and retention. Moreover, its heterogeneous effect sizes suggest that moderating effects exist. We advise

organizations to reconsider the value of CCT and those that desire to continue implementation should closely examine which configurations do and do not work. Similarly, no positive impact of interactions with other expatriates in non-work settings could be established. The effect on adjustment was insignificant and no other outcomes have been investigated in research (see Table 5.11 and Figure 5.3). If accelerated adjustment is the purpose of the expatriate club memberships organizations offer, our analyses suggest that interactions with HCN agents will be more effective. Moreover, isolation from HCN interactions via expatriate-only clubs, private schools, and closed compounds could even be harmful to the adjustment of expatriate families and thereby to assignment success. Organizations and scholars should team up to explore alternatives that expose expatriate families to interactions with the local community in a positive way.

5.6.6 Limitations

This meta-analysis is subject to several limitations. First, meta-analytical findings are limited by the design, methods, and rigor of the original studies. For example, all but a single study (Chen, Kirkman, Kim, Fahr, & Tangirala, 2010) have used cross-sectional survey data instead of a preferred longitudinal design and this limits the causal inferences we can draw based on our results. Poor performing or withdrawing expatriates could very well receive less support from their social environment as a consequence of their performance and not vice versa. Similarly, expatriates may appreciate their supervisor or organization more upon receiving a high performance rating whereas adjusted expatriates may better bond with local agents.

Although we demonstrated that rater effects and publication bias have not inflated effect sizes considerably, other factors may have had confounding effects. For example, previous international experiences, assignment hardship, or cross-cultural motivation may have influenced both the social support expatriates seek and receive as well as their attitudes to and behaviors in assignments. In light of this, the field of expatriate management research would benefit from more rigorous research designs. For example, longitudinal diary studies could be used to investigate how expatriates develop a host country social support network and how more/less established networks affect the different success criteria over time. Similarly, such designs may help to establish what types of support are most needed in the different phases of expatriation (e.g., career support around the end of the assignment). Quasi-experimental designs could be used to examine the effectiveness of global mobility practices. Organizations could cooperate and contribute data to a shared research project examining, for instance, the attitudes and behaviors of similar expatriates when paired with either host or home country mentors, after receiving different types of CCT, or with different allowance packages.

Second, there are some methodological limitations related to the small number of independent samples and the chosen meta-analytical model for some analyses. We believe that the true effect of social support on success criteria in expatriate studies may vary from one study to the next as often employees from a specific parent country (e.g., Kraimer & Wayne, 2004), in a specific host country (e.g., Lui & Ipe, 2010), or in specific occupations are considered (e.g., De Paul & Bikos, 2015). Random effects models were hence more appropriate than fixed effect models, as they assume a distribution of true

effects rather than a single true effect, thereby allowing small studies to contribute relatively more information (Borenstein, Higgings, Hedges, & Rothstein, 2009). However, we already had a relatively small number of independent samples for specific analyses and estimating random effects further decreased our statistical power. This may have contributed to the fact that we did not find evidence for some of our moderation hypotheses despite large differences in average effects. Therefore, we urge future scholars to examine more closely whether HCN and expatriate providers of social support and home and host country social support networks have differential effects on expatriates' cross-cultural adjustment and retention.

A final limitation is formed by the outcome variables included in this meta-analysis. We focused primarily on indicators that are relevant to the organization and, to some extent, to the expatriate, and thereby overlooked the interests of various other relevant stakeholders. Future research should include more indicators of success from the perspective of the family, such as work-life and work-family balance, the family's adjustment, career consequences for expatriate families, and their long-term happiness. Similarly, future research could examine to what extent international assignment causes positive effects for local stakeholders, for instance, the knowledge transfer to and development of the local organization, and whether these outweigh negative effects, for instance, the (perceived) injustice for local talents. This is important because, paraphrasing Suutari and Brewster (2003, p.1347), successful expatriation from an organizational perspective does not always entail success from the viewpoint of other stakeholders.

6 Paradoxes in global talent pipelines: HRM practices and graduate trainees' voluntary turnover

This chapter is submitted as van der Laken, P.A., van Veldhoven, M.J.P.M., & Paauwe, J. (n.d.). Paradoxes in global talent pipelines: HRM practices and graduate trainees' voluntary turnover.

Multinationals fill their talent pipelines with graduates hired into technical and managerial traineeships. We applied survival analysis to seven years (2010-2017) of Human Resources information system data of 9013 graduate recruits in two large multinationals to explore how performance, talent, and expatriate management relate to human capital loss. At both organizations, graduate trainees' voluntary turnover decreased with the favorability of performance evaluations whereas potential assessments had no incremental effect. Trainees were less likely to turnover voluntarily during short-term international assignment. However, at one organization, turnover risk increased after repatriation. Moreover, turnover rates and patterns differed significantly across organizational contexts.

6.1 Introduction

Western multinationals are recruiting large numbers of university graduates in the hope that these will one day form their top leadership teams (Stahl et al., 2012). Graduates happily join these organizations as they seek challenging jobs with opportunities for both personal and professional development, preferably in overseas or cross-cultural contexts (Festing & Shafer, 2014; Latukha, 2011; Tharenou, 2003). Nevertheless, multinationals face a significant challenge in retaining these young professionals and sustaining their global talent pipelines (Collings & Mellahi, 2009; Latukha, 2011; Stahl et al., 2012; Sturges, Guest, Conway, & Davey, 2002), resulting in high costs related to the replacement and loss of human capital (Cascio & Boudreau, 2010; Huselid & Becker, 2011).

Three human resources (HR) practices may help to segment and retain employees according to the human capital they resemble. First, relative performance evaluation systems help to rank and reward employees based on their contributions. These systems would attract skilled, high performing employees but repel those with less human capital (Blume, Baldwin, & Rubin, 2009; Griffeth & Hom, 2001; Nyberg, 2010; Steel, Griffeth, & Hom, 2002; Stewart, Gruys, & Storm, 2010). Second, leadership potential assessments are used to identify employees with high potential early on. High potentials often receive differential investments in their development and progression and such exclusive talent management would help attract, develop, and retain human capital (Björkman, Ehrnroooth, Mäkelä, Smale, & Sumelius, 2013; Dries & Pepermans, 2008; Hausknecht, Rodda, & Howard, 2009; Stahl et al., 2012). Third, multinationals use international assignments to transfer, develop, and retain their human capital. Short-term international assignments (STIA), lasting up to twelve months, are most frequently used to expatriate young professionals (Kang, Shen, & Benson, 2017; Shaffer, Kraimer, Chen, & Bolino, 2012). These STIA are considered a privilege and a development opportunity and may thus improve employee and talent retention, despite the lesser mobility support (Stahl et al., 2012; Steel et al., 2002; Tahvanainen, Welch, & Worm, 2005; Tsui, Pearce, Porter, & Tripoli, 1997).

However, hard evidence for the human capital implications of potential assessments and STIA is hitherto missing. Paradoxically, adverse effects may even exist. For instance, high potentials may perceive and pursue more external opportunities due to their talent status (De Cuyper & De Witte, 2011; Gelens, Hofmans, Dries, & Pepermans, 2014; Griffeth, Hom, & Gaertner, 2000) and adjustment- and career-related issues seems common during and after expatriation (e.g., Kraimer, Shaffer, & Bolino, 2009; Stahl, Chua, Caligiuri, Cerdin, & Taniguchi, 2009).

This study tracked 9013 new graduate recruits through the HR information systems (HRIS) of two large multinationals to explore how HRM practices affect trainees' turnover behavior. Our survival analysis with time-varying covariates (Therneau, Crowson, & Atkinson, 2017) allows us to establish how changes in performance evaluations, potential assessments, and international opportunities affect the duration of trainees' employment. Moreover, by collaborating with two large, truly global organizations, we explore how relations generalize across organizational contexts. On the one hand, our longitudinal analysis contributes to talent management research, where studies have hitherto focused

on employees' turnover intentions in cross-sectional designs instead of long-term behavior (Meyers, De Boeck, & Dries, 2017). On the other hand, we pioneer in exploring the implications of STIA, an increasingly popular form of expatriation (Baruch, Altman, & Tung, 2016; BGRS, 2015; Meyskens, Von Glinow, Werther, & Clarke, 2009).

6.2 Voluntary Turnover

Voluntary turnover – employee-initiated movements across the membership boundary of an organization – has been studied for over a century (Hom, Lee, Shaw, & Hausknecht, 2017). On the one hand, slowly developing, affective processes cause voluntary turnover. For example, employees leave organizations because of dissatisfaction, detachment, or poor performance (e.g., Allen & Griffeth, 1999; Mobley, Griffeth, Hand, & Meglino, 1979; Rubenstein, Eberly, Lee, & Mitchell, 2018; Steers & Mowday, 1981). On the other hand, so-called "*shocks*" cause turnover. Here, unsolicited job offers, family changes, or perceived value incongruences cause employees to leave impulsively (e.g., Holtom, Mitchell, Lee, & Eberly, 2008; Lee & Mitchell, 1994). In both cases, time plays an important role in modelling turnover and scholars increasingly conduct survival, hazard, and random coefficient models instead of the traditional logistic regression techniques to model patterns (e.g., Dickter, Roznowski, & Harrison, 1996; Kammeyer-Mueller, Wanberg, Glomb, & Ahlburg, 2005; Morita, Lee, & Mowday, 1993; Weller, Holtom, Matiaske, & Mellewigt, 2009).

6.3 HRM Practices

Organizations can reduce the costly voluntary turnover among their top talents via HRM practices. For instance, the implementation of "*high involvement*", "*high performance*", and "*high commitment*" practices – including performance management practices, developmental opportunities, and job enrichment – have been found to reduce turnover (Griffeth & Hom, 2001; Heavey, Holwerda, & Hausknecht, 2013; Jiang, Lepak, Hu, & Baer, 2012; Steel et al., 2002). These HRM practices continuously influence the employee-organization relationship and thereby affect the likelihood of voluntary turnover (Hom et al., 2009; Tsui et al., 1997). For graduate trainees in multinationals, particularly performance evaluations, potential assessments, and STIA are relevant. Frequently, other relevant HRM practices are standardized in national or global policies (e.g., base compensation; leave), leaving little variation within cohorts of peers. In contrast, performance systems, potential assessments, and STIA are implemented specifically with the purpose to differentiate within peer groups.

6.3.1 Performance Evaluation

Performance management systems help organizations to identify and reward the employees who contribute most to organizational goals while avoiding to appeal to those who do not (Griffeth & Hom, 2001; Steel et al., 2002). Frequently, systems with relative ratings are implemented to rank employees in a peer population, to overcome common rater errors, and to create a high-performance culture where financial and non-financial rewards are allocated on merit, without overspending on compensation budgets (Blume et al., 2009; Guralnik, Rozmarin, & So, 2004; Stewart et al., 2010). These relative systems

prevent human capital loss as high performers become less likely to leave. Their favorable performance evaluations function as positive feedback, publicly acknowledging employees' effort and capabilities (Blume et al., 2009). Moreover, high performers may expect a beneficial future at their current employer, including bonuses, promotions, and salary growth (Blume et al., 2009; Huselid, 1995). Expectancy theory (Vroom, 1964) states that employees are motivated to behave in ways that they expect will produce desirable outcomes. Hence, high performing employees will be less likely to abandon their desirable future whereas low-performing employees may seek better opportunities elsewhere. This inverse relationship between performance ratings and voluntary turnover has been established in general employee populations (e.g., Griffeth et al., 2000; Nyberg, 2010; Trevor, Gerhart, & Boudreau, 1997), resulting in the following hypothesis:

Hypothesis 1: Graduate trainees with more positive performance ratings are less likely to turnover voluntarily.

6.3.2 Leadership Potential

Leadership potential assessment forms the basis for the exclusive talent management programs with which organizations selectively invest in their most valuable and unique human capital (Dries & Pepermans, 2008; Iles, Chuai, & Preece, 2010; Stahl et al., 2012). Here, a limited proportion of an organization's workforce – those demonstrating sustained high performance, interpersonal skills, and other competencies – are recognized as having *high potential* to become the organization's most likely future leaders, and are henceforth treated as such (Consumer Goods, 2017; Dries, Van Acker, & Verbruggen, 2012; Iles et al., 2010; Shell, 2017). This status frequently comes with additional development opportunities – such as "*fast track*" career progression – whereas non-potential peers do not receive such preferential treatment (Björkman et al., 2013; Dries & Pepermans, 2008; Hausknecht et al., 2009).

Favorable leadership potential assessments can decrease turnover. Employees may perceive the high potential label and the consequent organizational investments in their development as long-term organizational commitments in the employment relationship (Björkman et al., 2013; Dries, Forrier, De Vos, & Pepermans, 2014; Dries & Pepermans, 2008; Gelens, Dries, Hofmans, & Pepermans, 2015; King, 2016). Such acts of organizational support fulfill the psychological contract and fuel the desire to remain employed (Allen, Shore, & Griffeth, 2003; Rousseau, 1995). Moreover, the label reflects employees' leadership capabilities, implies that these are valued by the organization, and that a prosperous future lies ahead (Gelens et al., 2015; Dries et al., 2012, 2014). Additionally, high potential status may increase employees' visibility in the organization, providing a career advantage. In light of expectancy theory (Vroom, 1964), favorable assessments could thus incentivize trainees to stay, leading to the following hypothesis:

Hypothesis 2a: Graduate trainees with more positive leadership potential ratings are less likely to turnover voluntarily.

Paradoxically, adverse turnover effects of potential assessment may also exist. First, favorable assessments may increase the career and developmental expectations employees have. Organizations that consequently provide insufficient opportunities break the psychological contract and may cause high potentials to explore alternatives (Gelens et al., 2014; Rousseau, 1995). Second, high potentials may (perceive to) become more valuable on the external labor market because of their status and the associated developmental programs, which makes them more likely to leave or be poached (De Cuyper & De Witte, 2011; Dries et al., 2014; Griffeth et al., 2000; Stahl et al., 2012). Although prior evidence favors a positive perspective, most studies have been cross-sectional and have disregarded important confounders such as performance evaluations (Björkman et al., 2013; Bethke-Langenegger, Mahler, & Staffelbach, 2011; De Cuyper & De Witte, 2011; Dries et al., 2012, 2014; Gelens et al., 2015; Ng & Feldman, 2008; Seopa, Wöcke, & Leeds, 2015). Hence, we pose the following hypothesis:

Hypothesis 2b: Graduate trainees with more positive leadership potential ratings are more likely to turnover voluntarily.

6.3.3 Short-term International Assignment

Increasingly, STIA functions as a less costly alternative to traditional, long-term expatriation (Baruch et al., 2016; BGRS, 2015; Meyskens et al., 2009). Lasting up to a year, STIA typically does not require or include family relocation. Additional cost efficiencies are realized by lesser compensation and administration as assignees often remain on home country salary, social security, and pension schemes (Collings, Scullion, & Morley, 2007; Kang et al., 2017; Tahvanainen et al., 2005). Consequently, STIA are faster and cheaper to deploy, administrate, maintain, and, potentially, terminate than traditional assignments (Tahvanainen et al., 2005).

STIA may bind graduate trainees to their organization. STIA are frequently reserved for the most talented employees and can therefore be considered a reward (Tahvanainen et al., 2005). Furthermore, the cross-cultural, developmental nature of the international assignment may fulfill the psychological contract of the trainee and send a strong signal of organizational support (Haslberger & Brewster, 2009; Latukha, 2011; Shaffer et al., 2012; Stahl, Miller, & Tung, 2002; Tharenou, 2003). On top of this, the capabilities acquired during STIA are often requirements for progression to upper management (Spreitzer, McCall, & Mahoney, 1997; Stahl et al., 2009; Suutari & Brewster, 2003), and such favorable prospects may improve retention (Vroom, 1964). This resulted in the following hypothesis:

Hypothesis 3a: Graduate trainees are less likely to turnover voluntarily as a result of STIA.

Paradoxically, STIA may also put assigned employees at risk. Increased turnover rates are commonly reported during traditional assignments, due to (family) adjustment issues on the one hand, and unmet career expectations and high market value upon return on the other hand (e.g., Black, Gregersen, Mendenhall, & Stroh, 1999; Bossard & Peterson, 2005; Kraimer et al., 2009; Lazarova & Caligiuri, 2001; Shaffer et al., 2012; Stahl et al.,

2002). With different assignment characteristics (i.e., short duration, development orientation, lesser rewards) and employee profiles (i.e., single, young assignees), the turnover implications of STIA are unknown. Hence, we pose the following alternative hypothesis:

Hypothesis 3b: Graduate trainees are more likely to turnover voluntarily as a result of STIA.

6.4 Methods

6.4.1 Sample Descriptions

At two multinationals, we tracked new graduate trainees through the HRIS for specific observational timeframes.

6.4.1.1 Consumer Goods

The first multinational requested to stay anonymous and will henceforth be referred to as Consumer Goods, as it operates in that sector. Consumer Goods employs over 150.000 employees in over 150 countries and has its headquarters in Western Europe. The observational timeframe lasted from January 1st, 2011 until March 31st, 2016 (63 months). The HRIS contained 2577 hiring records for graduate traineeships, 2538 (98.8%) of which represented unique joiners.[8].Yearly hiring patterns were stable, except for a hiring freeze in 2016. Recruits were mostly female (59.9%) and in the age band of 18 to 29 at hiring (98.4%). Most hires occurred in China (12.7%), India (10.4%), the USA (7.9%), the UK (7.6%), and Turkey (5.1%). All traineeships at Consumer Goods lasted three years.

6.4.1.2 Shell

The second multinational, Shell, is a group of companies operating in the oil and gas sector with its headquarters in the Netherlands. Shell operates in over 70 countries and employs around 92.000 employees globally (Shell, 2016). The observational timeframe at Shell lasted from January 1st, 2010 until May 31st, 2017 (89 months). The HRIS contained 6630 hiring records for graduate traineeships, 6475[9] (97.4%) of which represented unique joiners.[10] Yearly hiring patterns were stable. Recruits were mostly male (61.4%) and 25 years old on average (SD = 2.735). Most hires occurred in the USA (21.0%), the Netherlands (17.2%), Canada (9.5%), Malaysia (8.7%), and the UK (8.3%). Shell's

[8] Excluded from the Consumer Goods hiring data were seven records representing mergers and acquisitions, nineteen duplicate records due to split-time positions, seven duplicate records due to differing hiring dates (most recent record retained), and six non-graduate records identified by their age band and tenure.

[9] The sample used in the Cox proportional hazard models is slightly lower at $N = 6437$ (97.1%) because seven cases had no gender information and 31 ages were missing.

[10] Excluded from the Shell hiring data were fifteen records that had a missing or erroneous date of hire, 56 records representing mergers and acquisitions, 33 duplicate records due to a system error, 24 duplicate records due to differing job titles, fourteen duplicate records due to differing hiring dates (most recent record retained), and nine non-graduate hires identified by a combination of nationality and age.

technical traineeships (60.9%) lasted two to three years, commercial-oriented traineeships (18.5%) lasted between 2.5 and 4.5 years, and traineeships for corporate functions (18.0%) lasted three years.

6.4.2 Measures

6.4.2.1 Voluntary Turnover

We measured voluntary turnover using the duration of employment during the observational timeframe. Turnover was recorded on a daily level in Shell's HRIS, but on a monthly basis at Consumer Goods. During the observational timeframe at Consumer Goods, 496 trainees left voluntarily (19.6%) after a median 731 days. At Shell, 672 employees left (10.4%) after a median 850 days. We right-censored cases of involuntary turnover, including redundancies, divestments, and health-related contract endings (5.7% at Consumer Goods, 9.5% at Shell), and employees who were still employed at the end of our observational timeframes (74.6% at Consumer Goods, 80.1% at Shell), as is the convention in survival analysis (e.g., Nyberg, 2010).

6.4.2.2 Performance

At both organizations, supervisors recommended performance ratings for the end-of-year ranking panels, composed of the supervisors, HR business partners, and senior line managers of a peer population. This panel calibrated the final relative performance ranking of a population, with ratings following a forced distribution. Only employees who had joined before October were considered in the year's end calibration sessions (Consumer Goods, 2017; Shell, 2017).

At Consumer Goods, performance was evaluated on a five-point scale with a forced average of three. Unfortunately, data were sparse in 2011 and 2012. Graduates hired after 2012 received their first rating after a median 214 days and these matched the forced distribution ($M = 3.043$, $SD = 0.507$) with relatively underpopulated tails (0.7%, 7.9%, 78.9%, 11.7%, and 0.9% for ratings 1 through 5). In the full dataset, employees spent a median 426 days without rating and, for these 3987 records, the rating was replaced by the modal rating of 3.

At Shell, performance was evaluated on a decimal scale from 0.0 to 1.5 with a forced average of 1.03. Employees' first performance ratings matched the forced distribution ($M = 0.978$, $SD = 0.108$), with the majority of ratings either 0.9 (49.9%) or 1.0 (25.8%). Employees spent a median of 169 days without rating and, for these 7903 records, the rating was replaced by the modal rating of 0.9.

6.4.2.3 Leadership Potential

At both organizations, supervisors recommended potential ratings for their direct reports to calibration panels – composed of relevant managers, HR business partners, and senior line managers – who discussed employees alongside their peer population. The subsequent ratings were used to differentiate HRM processes, such as succession planning and learning and development (Consumer Goods, 2017; Shell, 2017).

At Consumer Goods, employees' potential was reviewed every end of year. Three labels were used – *no potential*, *emerging talent*, and *high potential*[11] – but employees defaulted to *no potential* upon hiring or promotions (Consumer Goods, 2017). Again, data were sparse in 2011 and 2012. The 1558 graduates hired afterwards received their first rating after a median of 245 days, resulting in 18.0% high potentials and 0.1% emerging talents.

At Shell, reviews had occurred bi-annually – in May of 2012, 2014, and 2016. Employees received one of four labels – reworded as *low, medium, high,* and *executive potential* – reflecting their potential for the respective management level. Employees were assessed only after their second employment anniversary, resulting in a high median of 1092 days before the first assessment. These first assessments were respectively 6.5% low, 42.6% middle, 47.1% upper, and 3.7% executive management potential. With no default category, we created five ordinal categories – low, middle, unassessed, upper, and executive potential – and added a dummy variable for those unassessed.

6.4.2.4 Short-term International Assignment

We operationalized short-term international assignments in two ways: (1) the current mobility status – STIA, repatriated, or local without prior STIA – and (2) the number of months an employee had spent on STIA for the organization, prior to their current position – i.e., international experience.

At Consumer Goods, 324 employees (12.8%) were assigned on at least one STIA during the observational timeframe, accumulating an average eight months of international experience (SD = 5.049). STIA commenced a median of 577 days after hiring and lasted a median of 182 days, with 6-month (19.3%) and 5-month assignments (9.9%) most common.

At Shell, 730 employees (11.5%) were assigned on at least one STIA during the observational timeframe, accumulating an average twelve months of international experience (SD = 6.271). STIA commenced a median 755 days after hiring and lasted a median of 364 days, with 12-month (35.8%) and 18-month assignments (11.3%) most common. In the latter cases, the longer assignments still fell under STIA policy as they were extended after their original 12-month duration.

6.4.2.5 Control Variables

From the HRIS, we retrieved additional demographic information on employees' gender, age (band) at hiring, current job level, hiring division, and base country. Advised by Consumer Goods, we also controlled for the developmental status of the countries' markets as more turnover was expected in developed markets. Advised by Shell, we also controlled for the orientation of the traineeship as less turnover was expected in technical traineeships.

[11] A fourth label existed (*High Performer*), but graduates could not receive this label due to the absence of a track record.

6.4.3 Analysis

Event history analysis (Allison, 1984) was conducted in the statistical software R (R Core Team, 2017) using the R package *survival* (Tharenou, 2015). We estimated the survival and hazard functions (Kaplan & Meier, 1958). The survival function (Equation 1) estimates, at time *t*, the probability that an employee stays beyond time *t*. Differences between the organizations' survival curves were assessed statistically using log-rank tests (Harrington & Fleming, 1982). The hazard function (Equation 2) estimates, at time *t*, the probability that an employee leaves given survival until time *t*.

$$(1)\ S(t) = Pr\{T \geq t\} = 1 - F(t) = \int_t^{\infty} f(x)dx$$

$$(2)\ \lambda(t) = \lim_{dt \to 0} \frac{Pr\{t \leq T < t + dt | T \geq t\}}{dt} dt$$

We conducted Cox proportional hazard regression models (Cox, 1972; Therneau & Grambsch, 2000) to estimate the association between survival time and multiple predictors simultaneously. Covariates for which employees had multiple time-dependent measurements were encoded as time-varying (Therneau et al., 2017). We used likelihood-ratio tests to assess model fit, where the test-statistic *D* is twice the difference in log-likelihood between the alternative and the null model (Wilks, 1938). We validate the proportional hazard assumption using scaled Schoenfeld residuals (Grambsch & Therneau, 1994).[12] We confirmed the robustness of our results by running our models using different strategies to handle missing values.[13]

6.5 Results

We conducted all analyses separately per organization. Table 6.1 displays the correlations among our main variables, but these are difficult to interpret due to the longitudinal nature of the data. At both organizations, voluntary turnover related negatively to performance ratings and tenure. At Consumer Goods, turnover also related negatively to international experience and potential ratings. While turnover related negatively to employees' age at Shell, turnover correlated positively to the higher age band dummy at Consumer Goods. Finally, at both organizations, positive associations existed between employees' performance, potential, and international experiences.

[12] Proportionality was not violated in the Consumer Goods data. At Shell, two country dummies demonstrated significant violations because eleven graduates in Nigeria turned over early ($t < 580$) whereas the only leaver in Gabon left late ($t = 2433$). This did not affect the results of our hypothesis tests.
[13] Results of hypothesis tests did not change when only complete cases were retained or when Shell's missing performance values were replaced by a rating of 1.0 instead of 0.9.

Table 6.1. Assymetrical correlation matrix for Shell (above diagonal) and Consumer Goods (under diagonal).

	1	2	3	4	5	6	7
1. Voluntary turnover[a]		.00	-.14***	-.06***	-.12***	-.02	-.02
2. Gender: Male	.00		.05***	.08***	.03**	-.02	.03*
3. Tenure[b]	-.06**	-.05*		.04**	.36***	.07***	.26***
4. Age[b]	.06**	.02	.03		-.04**	-.06***	-.06***
5. Performance[c]	-.09***	.05*	.21***	-.03		.44***	.18***
6. Potential[c]	-.07***	-.02	.14***	.04'	.28***		.14***
7. International exp.[a]	-.06**	.03	.23***	-.01	.16***	.22***	

Note: Consumer Goods (N = 2532) under diagonal, Shell (N = 6437) above diagonal.

[a] at final observation.

[b] band 18-29 = 0, band 30-39 = 1, at Consumer Goods; continuous at Shell.

[c] average score during observational timeframe.

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

6.5.1 Survival and Hazard Curves

Figure 6.1 displays the estimated survival over the course of the observational timeframes. Graduate trainees left Consumer Goods significantly more often and quickly than Shell ($\chi^2 = 374.13$, $p < .001$). Five years in, an estimated 45.8% of graduate recruits would have resigned at Consumer Goods compared to 14.7% at Shell.

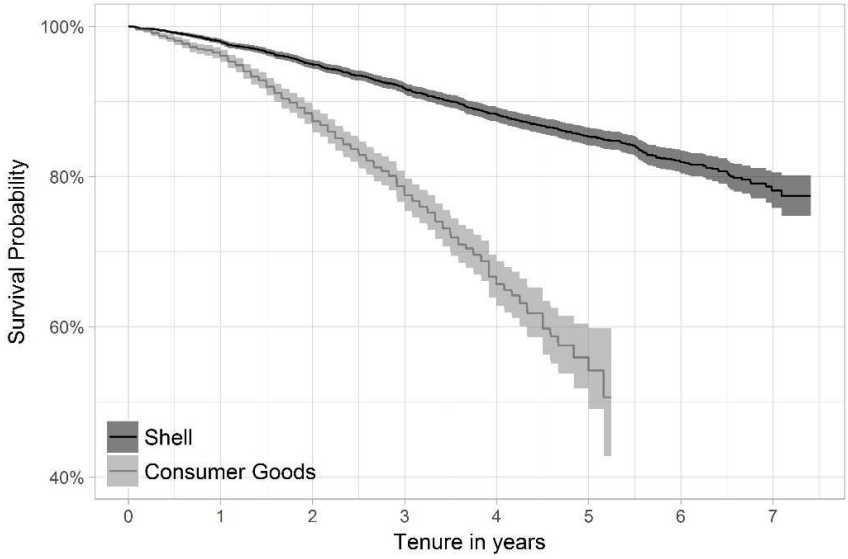

Figure 6.1. Estimated survival curves including 95% confidence interval.

6.5.2 Cox Proportional Hazard Regression

Tables 6.2 and 6.3 display the nested Cox proportional hazard regression models for respectively Consumer Goods and Shell. In line with Hypothesis 1, favorable performance evaluation had a strong negative influence on the voluntary turnover risk in the full

models (M3). Consumer Goods' employees became 1.52 times less likely[14] to leave with every point increase in performance (B = -0.42, p < .001) whereas Shell's employees became 1.45 times less likely to leave with every decimal point increase in performance (B = -3.73, p < .001).

Hypotheses 2a and 2b were rejected. Potential ratings did not affect graduate turnover at Consumer Goods (B = 0.01, p = .933) or Shell (B = -0.02, p = .817). Although potential related to decreased turnover in the second model at Shell (B = -0.22, p < .01), this effect disappeared when the other predictors were accounted for.[15]

In line with Hypothesis 3a, employees on STIA were 2.47 times less likely to leave Consumer Goods (B = -0.90, p < .05) and 3.77 times less likely to leave Shell (B = -1.33, p < .01), as compared to unassigned peers. However, this effect only lasted for the duration of the STIA as the accumulated amount of international experience had no effect at Consumer Goods (B = 0.02, p = .48) or Shell (B = -0.05, p = .057). In line with Hypothesis 3b, turnover was 2.29 times more likely among repatriates at Shell (B = 0.83, p < .01), but this was not found at Consumer Goods, where repatriates were not more or less likely to leave (B = -0.19, p = .71).

6.6 Discussion

We analyzed the voluntary turnover of 9013 graduate recruits for traineeships at two large multinational organizations – Consumer Goods (anonymized) and Shell – using survival analysis. Our results demonstrate that turnover patterns can vary considerably between organizational contexts – both in terms of the absolute numbers, the development over time, and the predictors. At both organizations, Cox proportional hazard regression models with time-varying covariates confirmed that employees' turnover decreased with the favorability of their performance evaluations. Although voluntary turnover among trainees was less likely during STIA, the amount of international experience accumulated had no effect. Paradoxically, employees at Shell became more likely to leave after repatriating from STIA. Finally, leadership potential assessments did not affect voluntary turnover after controlling for performance evaluations and international experiences. The next section discusses these findings in more detail, along with their implications, limitations, and avenues for future research.

[14] 1 – log(β)

[15] Inherently, unassessed Shell employees demonstrated increased hazard (B = 1.44, p < .001) because they had to have left early in the timeframe–before their first assessment, within 2 to 4 years after hiring.

Table 6.2. Cox proportional hazard models of voluntary turnover at Consumer Goods.

Consumer Goods	M1			M2.1			M2.2			M2.3			M3a		
	B	se	*p*	*B*	se	*p*	*B*	se	*p*	*B*	se	*p*	*B*	se	*p*
Gender (male)	0.15	0.10	.113	0.16	0.10	.090	0.15	0.10	.114	0.16	0.10	.092	0.17	0.10	.074
Age at hiring (30-39)[b]	0.31	0.30	.301	0.27	0.30	.362	0.30	0.30	.310	0.30	0.30	.316	0.26	0.30	.377
Performance rating[t]				-0.43***	0.11	.000							-0.42***	0.11	.000
Potential rating[t]							-0.06	0.079	.460				0.00	0.08	.933
Mobility status[tc]															
STIA										-0.95**	0.344	.006	-0.90**	0.35	.009
Repatriate										-0.17	0.344	.629	-0.13	0.35	.714
STIA experience[t]										0.02	0.031	.468	0.02	0.03	.480
Log likelihood	-3390.65		.000	-3383.18		.000	-3390.37		.000	-3385.03		.000	-3378.12		.000
Parameters	31			32			32			34			36		
D **(χ^2)**				14.95***		.000	0.55		.457	11.23*		.011	10.10*		.039

Note: Other covariates included, but not printed: hiring year, organizational division, base country, market status, and work level.

[a] M3 is compared statistically to M2.1.

[t] time-varying.

[b] referent = 18 – 29.

[c] referent = local and no international experience.

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

Table 6.3. Cox proportional hazard models of voluntary turnover at Shell.

Shell	**M1**			**M2.1**			**M2.2**			**M2.3**			**M3[a]**		
	B	se	*p*	*B*	se	*p*	*B*	se	*p*	*B*	se	*p*	*B*	se	*p*
Gender (male)	0.06	0.08	.469	0.10	0.08	.228	0.06	0.08	.513	0.07	0.08	.382	0.10	0.08	.240
Age at hiring[b]	-0.03	0.02	.055	-0.05**	0.02	.004	-0.03	0.02	.052	-0.04*	0.02	.034	-0.05**	0.02	.004
Performance rating[t]				-3.78***	0.27	.000							-3.73***	0.28	.000
Potential rating[t]							-0.22**	0.07	.003				-0.02	0.07	.817
Potential unassessed[t]							1.49***	0.16	.000				1.44***	0.16	.000
Mobility status[tc]															
STIA										-1.51***	0.41	.000	-1.33**	0.41	.001
Repatriate										0.67*	0.32	.037	0.83**	0.32	.010
STIA experience[t]										-0.04	0.03	.101	-0.05	0.03	.057
Log likelihood	-5248.37		.000	-5159.67		.000	-5199.68		.000	-5233.15		.000	-5104.07		.000
Parameters	38			39			40			41			44		
D **(χ^2)**				177.38***		.000	97.38***		.000	30.43***		.000	111.20***		.000

Note: Other covariates included, but not printed: hiring year, organizational division, base country, skill pool, and work level.

[a] M3 is compared statistically to M2.1.

[t] time-varying.

[b] continuous, in years.

[c] referent = local and no international experience.

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

6.6.1 Turnover in Context

Considerable differences existed between the organizations' turnover rates. Both Consumer Goods and Shell extensively promoted their traineeships at university campuses in order to recruit fresh graduates. Voluntary turnover among recruited trainees seems less of an issue at Shell, where turnover rates ranged between 2% and 4% annually. In contrast, Consumer Goods experienced more leakage in their talent pipeline, with rates ranging between 4% and 12% annually during our observational period. Yet, Consumer Goods appears relatively capable of retaining its employees in comparison to the wider consumer goods sector, where annual turnover rates range anywhere between 6%, 13% (Mercer, 2015), and 18% annually (Bureau of Labor Statistics, 2016). Potentially, these fast-paced consumer markets (Mercer, 2015) attract employees with a different mindset (e.g., more opportunistic) and thus requires the shorter-term-oriented HRM policies (e.g., talent status until promotion). Shell's turnover rate remains low even when viewed in light of the broader oil and gas industry (Mercer, 2015; Bureau of Labor Statistics, 2016).

Looking at the development of the turnover rates, both organizations experience low turnover at the start of traineeships (Figure 6.1). Afterwards, the turnover rate increases linearly at Consumer Goods, but curvilinear at Shell, the hazard function demonstrated. While such differences cannot be explained based on our current data, they do have implications for the viability of management strategies. For instance, from a resource-based perspective (Barney, 2001), oil and gas majors such as Shell reap the long-term benefits of its investments in graduate personnel whereas, in the consumer goods industry, organizations seem to develop talent in part for the competition.

6.6.2 Performance

High performing trainees were less likely to turnover voluntarily in both organizations, in line with Hypothesis 1. Similar effects have been found in other employee cohorts (e.g., Griffeth et al., 2000; Nyberg, 2010). The financial and career benefits linked to performance systems along with the appraisal and visibility may incentivize high performers to stay. Nevertheless, the consequent sorting effect may not necessarily be good news. First, the enforced normal distribution of performance ratings may not resemble the underlying true distribution of employee performance (see Beck, Beatty, & Sackett, 2014; O'Boyle Jr. & Aguinis, 2012). This could cause employees to leave because of relatively low ratings whereas they actually demonstrate high performance, or vice versa. Second, the definition of high performance within relative rating systems is not stable over time. Leaving low-performers raise the (real) average of peer cohorts to a point where previous high performers will become average and thus incentivized to leave. This "*up-or-out*" principle or "*tournament model*" (Rosenbaum, 1984) may not be viable in departments with many non-strategic positions (Huselid & Becker, 2011) or in contexts with stable peer groups, such as network organizations.

6.6.3 Leadership Potential

In contrast to Hypotheses 2a and 2b, leadership potential assessments did not affect turnover at either organization and we propose three explanations. First, potential assessments may indeed not affect turnover. Prior studies that found improved commitment and retention among high potentials did often not control for performance evaluations and employed a cross-sectional design (e.g., Björkman et al., 2013; Dries et al., 2012). Our longitudinal results did demonstrate the same positive effect of potential ratings, but only when performance evaluations and STIA were not considered. Once these other important predictors were included, potential ratings no longer influenced retention in our study. Hence, prior research might have mistakenly attributed improved retention to potential status whereas its actual cause was a confounding variable, such as performance evaluation, affecting both employees' potential ratings and their retention.

Second, opposing effects may be at play. Favorable potential assessments lead to increased employability resources, causing employees to perceive more and more easily attainable career opportunities (Dries et al., 2014). However, these opportunities may not necessarily lie within the current organization (De Cuyper & De Witte, 2011). If talents perceive more opportunities in- and outside of their current organization, this could result in a zero-net retention effect, which explains why we, and others before us (e.g., Dries et al., 2014), have not found increased loyalty among high potentials.

Finally, the relationship between potential and turnover may depend on the perceived or received rewards. Although both talent management policies stated that additional developmental opportunities were given to high potential employees (e.g., access to specific courses), career progression was not guaranteed in either organization. Consumer Goods documentation stated that *"being listed [as High Potential] is no guarantee of a bigger opportunity [...] and this can prove frustrating*" (2017, p. 71). Similarly, over half of Shell's trainees was assessed with potential for upper or executive management already in their first cycle. This proportion is nowhere near the number of open leadership positions at those organizational levels. Nevertheless, high potentials may interpret their talent status as a promise by their organization (King, 2016). Not meeting these expectations could cause talents to leave. High potentials may become convinced of their own capabilities, perceive opportunities on the external market, and thus seek alternatives if they are not rewarded according to their expectations.

6.6.4 Short-term International Assignment

STIA affected trainees' turnover in more complex ways than expected. In line with Hypothesis 3a, employees on STIA were 2.5 to 3.8 times less likely to leave, at Consumer Goods and at Shell, respectively. The challenging overseas roles may have fostered personal and professional growth on which young professionals willingly capitalized. Simultaneously, assignees may have perceived increased barriers to turnover as the overseas move increased their psychological investment in the job and organization. Turnover during STIA would have implied a loss of the developmental opportunities and the associated status, making termination costly from financial, career, and psychological perspectives.

However, this effect was limited to the STIA duration and two additional results suggest that STIA does not necessarily improve talent retention. First, the amount of international experience did not affect employees' turnover at either organization. We had expected that organizations and employees would seek to leverage such experience (Haslberger & Brewster, 2009). Scholars have suggested that a single international experience can be equally or more valuable than multiple, consecutive assignments (Bolino, 2007; Kraimer et al., 2009). Here, more time abroad may not improve retention as employees become detached from their parent organization, its culture and its leadership team (Bolino, 2007; Selmer, 2002; Peltonen, 1997). Alternatively, the value of STIA experiences could have depended on the jobs' responsibilities, the distance to headquarters, or the level of hardship (Bolino, 2007; Stahl et al., 2009). Potentially only a few, specific international experiences improved trainees' retention.

Second and paradoxically, repatriates at Shell became over twice as likely to leave as compared to their unassigned peers. This finding matches the high turnover rates reported among traditional repatriates (e.g., Lazarova & Caligiuri, 2001), but was not replicated at Consumer Goods. Here, assignment duration may provide an explanation: the median STIA at Shell lasted twice as long as those at Consumer Goods – twelve instead of six months. Assignees at Shell thus endured the overseas adjustment challenges and disrupted social networks longer, often exceeding the original 12-month STIA duration. This may have demanded larger personal investments from expatriates, resulting in stronger reward expectations and contract imbalance upon repatriation, which many studies have linked to increased search for alternative employment (e.g., Kraimer et al., 2009; Kraimer, Shaffer, Harrison, & Ren, 2012; Lazarova & Caligiuri, 2001; Vidal, Valle, & Aragón, 2007). Moreover, as discussed earlier, assignees on prolonged overseas stays may have become detached from the home organization (Bolino, 2007; Peltonen, 1997; Selmer, 2002), resulting in more turnover upon return. Alternatively, the difference could be a matter of organizational context, where differences in repatriate management practices explain the repatriate turnover. Unfortunately, we lacked detailed and objective information to compare these practices across organizations and follow-up research, for instance, using qualitative comparative analysis, would be valuable.

6.6.5 Practical Implications

The current study has four main implications for practice. First, we reiterate that relative performance evaluation can help organizations retain their talents and repel poor performers. Systems should thus be designed to leverage such benefits. Ratings should be as objective as possible, closely resembling the desired behaviors, and organizations should consider what distribution of scores best approximates actual differences in employee performance. We acknowledge that these are challenging tasks.

Second, organizations should assess their current approach to talent management. While the organizations in this study managed and assessed talent differently, neither exclusive approach improved talent retention. In general, organizations should be cautious in classifying potential as the ratings may send strong signals, raising or lowering employees' expectations. Without clear expectation management or actual career opportunities, potential assessment could have adverse effects. Alternatively,

organizations may want to explore more inclusive approaches to talent management (e.g., Meyers, De Boeck, & Dries, 2017).

Third, organizations could use STIA to prepare young talents for future global leadership, as long as close attention is paid to the repatriation process. Otherwise, STIA may merely delay or even boost talent loss. Rigorous workforce, career, and succession planning should help to identify suitable positions for repatriates. Better expectation management could prevent false expectations regarding the benefits of STIA for career advancement. Here, employees could take on a proactive role themselves in revealing their personal expectations. On top of this, organizations could experiment with shorter assignments instead of sending the same employees on long or consecutive STIA as our results and others (e.g., Kraimer et al., 2009) hint this may improve talent retention.

Finally, organizations may seek to replicate the current analysis within their own population to examine how, when, and where they can improve the sustainability of talent pipelines in their own context. The capability to pinpoint when and why turnover risk is high may permit timely intervention and more sustainable investment in young talent. Here, extensions of the current model with internal data – for instance, on selection tests, compensation, development, and organizational changes – and external information – such as (labor) market characteristics – could prove valuable.

6.6.6 Future Research and Limitations

This study is subject to several limitations. First, despite our longitudinal data, establishing causality remains difficult. For instance, instead of low performance causing voluntary turnover, both may be the result of trainees' early withdrawal behaviors from the job and organization. Additionally, the strong and complex relationships among employees' performance, potential, international experiences, and other HRM variables (e.g., salary, promotions) warrant more focused longitudinal research to establish their precise effects on turnover.

Second, archival data have their limitations. Inherently, employees do not have performance and potential ratings until they undergo the respective evaluation or assessment. This implied that the HRIS lacked certain data for the early period of all trainees' careers. We opted to replace these early missing data points with the modal rating in each organization; an alternative was to disregard all observations during this early period. While the results of our hypothesis test remained the same, either approach introduced its own potential biases. A replication of our study using other data sources may be valuable.

Third, our results demonstrated that turnover is affected by contextual factors and a more detailed exploration is warranted here. While we controlled for direct country- and organizational-level effects on turnover, we did not model country-level moderations related to labor market characteristics or cultural preferences for and attitudes to talent strategies (Farndale, Scullion, & Sparrow, 2010). Similarly, STIA may have different implications because of home and host country locations or the differences between them. Future research should consider more closely how turnover and its predictors differ across contexts.

Finally, the current study only considered STIA, but not the time spent on traditional long-term, self-initiated, local-plus, or commuter assignments. Future research should examine how these other forms of expatriation affect the psychological contracts, the careers, and the voluntary turnover of young professionals.

7 Discussion

This dissertation explored people analytics and its application to expatriate management through its seven Chapters. Chapter 1 introduced the concept of people analytics, elaborating on the contemporary rise in workforce data and analytical capabilities and their potential for evidence-based HRM. Chapter 2 explored the state of analytics usage in functional management disciplines, thus comparing people analytics to other applications of analytics. Chapter 3 discussed and illustrated how unconventional analysis can help to distill value from novel HRM data formats produced by digital technology. Chapters 4 explored the indicators of successful expatriation and how these are affected by organizational agents. Chapter 5 continued this line of research, quantifying the basis of evidence for various types of global mobility support during the expatriation process. Finally, Chapter 6 provided an applied example of people analytics to, among others, the topic of expatriate management. This study sought to quantify the impact of short-term expatriation and other HRM practices on employee retention, approaching HRIS data with scientific rigor.

In this seventh Chapter, I first summarize the main findings regarding this dissertation's two research questions: "What is the current state of people analytics?" and "How can people analytics make HRM more evidence-based?" Subsequently, I provide a general discussion on the future of people analytics where I elaborate on the current research streams, the bridges people analytics may form, the ethical and privacy concerns related to people analytics, the machine learning principles from which the HRM domain may benefit, and the viability of an HR-specific analytics function. This dissertation concludes with a discussion of its implications for science and practice and several specific avenues for future research on people analytics.

7.1 RQ1: Slow Rise of People Analytics

The first research question of this dissertation was "*What is the current state of people analytics?*" During this PhD project, I have dived into the scientific discourse on data analytics in general and of people analytics in specific, and I have implemented people analytics projects in practice. Unfortunately, I cannot but conclude that, in general, the HRM domain – including the HRM function in practice as well as the scientific HRM research community – is trailing behind other functional management domains when it comes to generating value through data analytics.

7.1.1 Trailing Behind

In Chapter 2, I conclude that the use of analytics and machine learning is less common in relation to HRM in comparison to other functional management domains. This is visible in the scientific publication networks of studies that have examined big data, analytics, and machine learning and their implications for the performance in and of organizations. Currently, analytics is contributing business value particularly in the functional domains of marketing, finance, information technology, and supply chain. More often than in HRM, advanced data analytics applications such as text mining, predictive modelling, and machine learning are already leveraged in these domains (Chapter 2). Despite specifically searching for keywords such as "*employee-*", "*worker-*" and "*team performance*", similar developments were not directly visible in the field of HRM. People analytics, HRM research, the HRM function, nor employee data appeared prominently in the publication networks on data analytics.

However, this does not imply that there are no developments regarding data analytics in the HRM domain at all. A closer inspection of the content of the primary studies included in Chapter 2 reinforces the assumption that applications of people analytics are becoming more widespread. A small fragment of the included studies explored the value of employee-, team-, and HRM-related data in improving business processes through analytics and machine learning (e.g., Aral, Brynjolfsson, & Wu, 2012; Baba, Kashima, Kinoshita, Yamaguchi, & Akiyoshi, 2012; Colley & Neal, 2012; Johnson & Gonzalez, 2014; Kontogiannis & Kossiavelou, 1999; Lam, Sleep, Hennig-Thurau, Sridhar, & Saboo, 2017; Robinson, Alifantis, Edwards, Ladbrook, & Waller, 2005; Tan & Netessine, 2014). Moreover, many scientific studies have explored applications of advanced analytics within an HRM context, but have been published outside of the management literature (e.g., Strohmeier & Piazza, 2013), whereas developments in practice may simply not have been published academically at all. Overall, Chapter 2 underlines that analytics and machine learning in the HRM domain is still undergoing development and that scholarly discussion on HR-related data analytics and its implications for organizations and employees is still in a startup phase.

7.1.2 Methodological Inflexibility

In part, the HRM domain may be trailing behind due to the methodological inflexibility of the field. Historically, the HRM domain has not been associated with extensive quantitative analysis. Professionals and scholars have addressed the lack of analytical and statistical capabilities among contemporary HRM professionals (e.g.,

Angrave et al., 2016; Bassi, 2011; Boudreau & Ramstad, 2007; Mondare, Douhitt, & Carson, 2011; Roberts, 2009; Schramm, 2006; Zielinski, 2014). This limited statistical savviness would have hampered the spread of people analytics in practice (Angrave et al., 2016; Cascio & Boudreau, 2010; Paauwe & Farndale, 2017).

Similarly, the scientific community can be argued to trail behind because of their reliance on associative measures and explanatory modeling. Like other social science fields, the majority of HRM research is conducted via ordinary least squares regression analysis on structured, theory-driven datasets collected via cross-sectional questionnaires. Such analyses are in line with the traditional purpose of HRM research: the generation of explanatory management theories. Nevertheless, even the quality of these explanatory theories can improve once scholars become more open to alternative analytical strategies and techniques (see section 7.3.4 on Machine Learning; Shmueli, 2010; Yarkoni & Westfall, 2017).

The purpose of people analytics – to gain actionable insights, potentially using novel, complex forms of HRM data – often requires alternative methodological approaches. Hence, people analytics projects often take a more inductive approach to explore which relationships exist in the data, rather than using the data to confirm scientific theories (Chapter 1; Chapter 3). People analytics researchers are often specifically concerned with how well a model performs on "new", unseen data (e.g., predictive accuracy) whereas how well models fit – or explain variance – in the current sample (e.g., information criteria, R^2) can be of secondary importance. Optimizing this predictive accuracy of a model requires a different workflow than the one common in conventional HRM research. For instance, people analytics researchers may use cross-validation and bootstrapping in order to train, test, and validate models on partitions of the data (Friedman, Hastie, & Tibshirani, 2001; James et al., 2013; Shmeuli, 2010; Yarkoni & Westfall, 2017). Additionally, this different purpose opens the floor for unconventional statistical models and data mining algorithms that trade off explanatory value and interpretability for predictive accuracy and exploratory capability. Examples include shrinkage (e.g., ridge regression), ensemble (e.g., bagging, boosting), deep learning (e.g., neural networks), Bayesian, and graphical methods (Friedman et al., 2001; James et al., 2013; Jebb, Parrigon, & Woo, 2016; Shmeuli, 2010; Woo et al., 2017; Yarkoni & Westfall, 2017). Such non-traditional methods and workflow can help to uncover new practical and scientific insights and improve the quality of HRM decisions.

In this dissertation specifically, I applied network analysis to explore communication channels (Chapter 2) and survival analysis techniques to uncover turnover patterns and the effect of HRM practices thereon (Chapter 6). Both are infrequently applied in conventional HRM research, despite their applicability to a wide range of HRM topics (e.g., onboarding, succession planning). Furthermore, Chapter 3 illustrates how latent class analysis – or bathtub modeling (Croon et al., 2014) – helps to overcome multi-level issues in the HRM-performance relationship and how optimal

matching analysis helps to gain insights from new high volume and high velocity HRM data formats, such the data gathered via continuous listening.[16]

Researchers outside of scholarly HRM communities are already leveraging the value of these new methods in the HRM domain. Data mining scholars are using decision trees, cluster analysis, association analysis, support vector machines, and neural networks to solve HRM issues related to employee selection, development, and turnover, performance management and reward allocation, and career and cost planning (Strohmeier & Piazza, 2013, p. 2410). Similarly, Chapter 2 demonstrated that scholars are optimizing work conditions for well-being and productivity using sales and scheduling data (Tan & Netessine, 2014), improving team behaviors via machine learning (Johnson & Gonzalez, 2014), and evaluating safety climates by text mining employee interviews (Colley & Neal, 2012). Moreover, HRM data scientists and people analytics analysts in practice are applying advanced analytics to solve a variety of HRM issues. To illustrate, my direct colleagues in Shell have quantified team diversity in a multi-dimensional fashion via multiple correspondence analysis (Bongenaar & Van Leeuwen, 2016), predicted cyber security risks via tree-based models (Giagkoulas & Hawkes, 2016), digitized recruitment and assessment processes (Lam & Hawkes, 2017), and many more (Van der Togt & Rasmussen, 2017). However, such applications seem less widespread in mainstream HRM practitioner and scientific communities.

7.1.3 RQ1: Intermediate Conclusion & Future Directions

In conclusion, the spread of analytics seems slow within the HRM domain. Chapter 2 demonstrated that business value through data analytics and machine learning applications is achieved more frequently in other functional domains. HRM scholars and practitioners are often not familiar with the different methodological approaches that are needed for people analytics and the analysis of complex data formats (Chapter 3). While there are visible developments related to people analytics in scientific and practitioner communities (Chapter 2), the overall adoption is slow.

These are early conclusions on limited research and further exploration via alternative designs, angles, and perspectives would be valuable. Chapter 2 relied on open-access data on scientific publication networks. Here, organization-level surveys regarding the use of, or familiarity with, (big) data, analytics, and algorithmic intelligence in the different functional management domains would have been a great addition in light of my first research question. Similarly, instead of exploring potential methodological applications, such as in Chapter 3, it would have been valuable to study the perceptions and knowledge of scholars and practitioners regarding different research designs, methods, and algorithms. In both cases, it would have been valuable to discriminate more explicitly between the rise of (people) analytics in HRM research and practitioner communities.

[16] Process whereby organizations gather structured or unstructured data, such as employee experiences or feedback, at relatively frequent intervals (e.g., hourly, daily, weekly).

7.2 RQ2: People Analytics facilitates Evidence-Based Expatriate Management

The second research question of this dissertation – "*How can people analytics make HRM more evidence-based?*" – was approached via an application of people analytics to the specific case of expatriate management. In three steps, this dissertation explored how HRM on specifically this topic could become more evidence-based. First, success or impact had to be quantified. Next, general best practices were identified by aggregating conventional research findings. Third, local impact could be quantified via analysis within the organizational contexts. These steps resemble the general process of any people analytics project.

7.2.1 Quantifying Impact

In order to make informed, data-driven HRM decisions, one first needs to establish how the success or the impact of HRM can measured. The effect of expatriate management on operational and financial outcomes is hard to grasp in practice (BGRS, 2015, 2016; McNulty & Tharenou, 2004). Instead, scholars have explored a broad range of work and psychological outcomes related to expatriation, including stress and adjustment (e.g., Shaffer et al., 1999; Takeuchi, Wang, & Marinova, 2005), performance (e.g., Kraimer et al., 2001), turnover (e.g., Kraimer et al., 2012), career implications (e.g., Ren, Bolino, Shaffer, & Kraimer, 2013), and family well-being (e.g., Takeuchi et al., 2002). On the bright side, the impact of expatriate management is measureable and scholars have taken a balanced approach.

On the dark side, the large diversity of studies, outcomes, and samples makes it hard to identify best practices. Expatriate management research is plagued by small and diverse samples: expatriates are hard to find in large numbers and they vary strongly in terms of their characteristics (e.g., host country, home country, nationality, assignment type, assignment purpose, sector). Along with the variety of outcomes under study, this introduces difficulties regarding generalization. Potentially as a consequence, expatriate management in practice is not very quantitative or evidence-based (BGRS, 2015, 2016).

7.2.2 General Best Practices via Conventional HRM Research

A systematic review of literature functions as a first basis of evidence for expatriate management effectiveness (Rousseau & Barends, 2011). Chapter 4 explores literature on organizational actors in the expatriation process and their influences on indicators of expatriate success. This review identified various organizational stakeholders (e.g., HRM practices, supervisors, mentors, peers; Chapter 4), the outcomes they influence (e.g., satisfaction, adjustment, performance, commitment, retention), as well as the theoretical underpinning explaining why (e.g., stress management, social exchange, social capital; Chapter 4). A more quantitative approach was needed to establish the exact relevance of each of these stakeholders and their support. Hence, Chapter 5 sought to meta-analytically summarize the findings of 84 independent scientific studies. Some earlier attempts had already facilitated a basis of evidence, but focused on specific practices or specific outcomes of expatriation (Bhaskar-Shrinivas et al., 2005; Littrell, Salas, Hess, Paley, & Riedel, 2006; Mol, Born, Willemsen, & Van der Molen, 2005). In contrast, Chapter

5 provides estimates for the impact of HRM practices, and the social relationships related to these practices, on multiple indicators of expatriate success.

Overall, the meta-analysis provided quite a comprehensive overview of the actors in the expatriation process and their differential effects on indicators of success. Most surprisingly, mentoring and logistical support (e.g., preview trips) related to expatriates' performance but not to their retention. In line with my expectations, expatriates' perceptions of organizational and supervisory support were most important for assignment success closely followed by support from the family – in particular the spouse. The results disproved the common assumption that cross-cultural training and social relations with other expatriates relate to expatriates' performance or retention (Chapter 5). Such general evidence-based insights help organizations in the first steps towards improving expatriate management initiatives in their own context. These results complement human intuition and expert knowledge by demonstrating to what extent practices have been effective in other contexts (i.e., effect size), and have been similarly effective across different contexts (e.g., confidence interval).

7.2.3 Local Impact through People Analytics

However, for decision-making, we prefer evidence-based insights that are relevant specifically within the local, organizational context. While conventional HRM research provides general knowledge, the problems HRM professionals face are always unique and specific (Van Aken, 2004, p. 226). Hence, in Chapter 6, I explore how scholars and practitioners could apply people analytics to quantify the impact of expatriation locally. For this, I could make convenient use of the longitudinal employee data that is already stored in contemporary HRIS. Extensive data transformations and complex survival analysis quantified the change in employee turnover following short-term expatriation and repatriation, controlling for other factors. The results demonstrate that employees at both multinationals were highly unlikely to leave during their STIA. Compared to their peers in local positions, assignees demonstrated a turnover rate that was 2.5 to 4 times lower. In this sense, short-term expatriation had thus helped the organizations to retain their talent, an outcome that had not previously been researched in either science or practice (Kang et al., 2017; Tahvanainen et al., 2005).

Additionally, the results of Chapter 6 underline the importance of the contextual validation that people analytics implies. At one of the two multinationals, the turnover rate became over two times as high after employees returned from STIA, as compared to their unassigned peers. Via people analytics, I could thus evidence that short-term expatriation, in its current form at this second organization, delayed turnover for the duration of the international assignment, but may not be the best talent management practice in the long term. Although I could not establish the exact reason for these patterns without follow-up (qualitative) research within the organization, the mere knowledge of this increased turnover already provides reason for internal discussion regarding the benefits of expatriation, the use and monitoring of international assignment, and the necessary next steps to uncover more detailed insights to base future decisions on.

7.2.4 RQ2: Intermediate Conclusion & Future Directions

In conclusion, this dissertation explored how people analytics can stimulate evidence-based HRM in practice, illustrated by an application to expatriate management. First, Chapters 4 and 5 demonstrated how scientific literature can be leveraged to explore a quantification of HRM impact. Next, Chapter 5 specifically demonstrated how to identify and quantify the impact of general best practices. Finally, Chapter 6 illustrated how people analytics may help to quantify the local impact of HRM practices through the analysis of longitudinal HRIS data in the own, organizational context.

This dissertation only touched the surface of the potential applications and implications of people analytics for expatriate management. For instance, the chapters of this dissertation mostly follow the conventional research process associated with basic science (e.g., theory-driven explanatory modelling) rather than following an applied science or design science approach (see Simon, 2001; Van Aken, 2004). I did conduct several predictive and exploratory projects during the past four years, also on the topic of expatriate management (e.g., predicting likelihood of expatriate success; exploratory network analysis on successful international moves). However, we did not turn these projects into scientific papers because of our impression that contemporary management and psychology journals would not be interested in publishing such research. Such impressions result in a self-fullfilling and reinforcing cycle indeed keeping applied and design science projects out of HRM journals. We hope that in the future, scientific culture will change in such a way that scholarly communities become more open to and accepting of these forms of research.

A second deduction, in hindsight, is that my dissertation is fixated on the success of international assignments in the eyes of the organization and, in part, the expatriate. Prior to Chapters 4 and 5, it would have been interesting to explore what different stakeholders (e.g., expatriates, families, organizations, supervisors, colleagues, local communities) consider to be *expatriate success*. Here, interviews regarding success and failure cases – combined with text analysis – could have helped to create a more holistic measure of success. Similarly, Chapter 6 was limited to short-term assignments and their impact on retention. It would have been more interesting to explore other types of assignment (e.g., commuting, long-term) and their effects on alternative outcomes, such as performance, career progression, knowledge-sharing, or (family) well-being.

7.3 People Analytics and the Future of HRM

The following section discusses several topics related to the future of people analytics. First, I elaborate on the presence of people analytics in the current scientific literature. Second, I discuss people analytics' potential to form bridges between and within communities in science and practice. Third, I elaborate on the difficult ethical questions regarding how HRM data can and should be collected and processed. Fourth, I discuss machine learning principles and what they could bring to the HRM domain in general. Fifth and finally, I compare the added value of the current approach to people analytics in light of the (dis)advantages of integration within a centralized business analytics function.

7.3.1 Fragmented People Analytics Research

Although not specifically substantiated in any of the chapters of this dissertation, I discovered that scientific research on people analytics and data-driven HRM has developed into multiple, mostly isolated streams of literature. The next section discusses these streams one by one, before demonstrating the ambiguity this fragmentation creates.

7.3.1.1 Conventional HRM research

In general, most quantitative HRM research provides some form of evidence for the optimal management and organization of employees, thereby at least partially fitting the common definition of people analytics (e.g., Marler & Boudreau, 2017). However, some HRM studies appears more closely related to people analytics than others. Wright and Boswell (2002) divided conventional HRM research into four subcategories, based on the level of analysis (organization vs. individual) and the number of HRM practices considered in the study (multiple vs. single). In light of people analytics, particularly the level of analysis seems an important research characteristic.

The level of analysis determines the granularity of the insights a research project produces. HRM research on the organizational level (e.g., research on strategic HRM, industrial relations, high-performance work systems, and isolated functions in Wright & Boswell, 2002) has explained how HRM implementation affects employees' behaviors and cognitions and, in turn, their well-being and performance (e.g., Harter et al., 2002; Jiang et al., 2012; Van de Voorde, Paauwe, & Van Veldhoven, 2010). Such macro-level insights provide a general basis of evidence for best practices and are very relevant in the scoping phase of any people analytics project (e.g., Chapter 5). However, they infrequently provide direct evidence for local, contextual impact of HRM activities. HRM research aimed at the micro-level (e.g., research on psychological contract, employment relationship, functional HRM, and I/O psychology in Wright & Boswell, 2002) may establish this local impact when large samples of a single organizational population are included. These studies can provide the local, evidence-based insights that hold direct value in HRM decision-making in practice (e.g., Chapter 6). Hence, particularly conventional micro-level HRM research closely fits the definition of people analytics. However, even for micro-level HRM research, the purpose will often starkly differ from that of people analytics. As discussed in Chapter 1, by tradition, the statistical modeling process will often be a testament to this. In sum, conventional HRM research only partially fits the common definitions of applied people analytics and some studies more than others.

7.3.1.2 People Analytics Literature

Second, scholars in scientific and semi-scientific journals have discussed specifically people analytics (Marler & Boudreau, 2017) and big data initiatives in the HRM domain (e.g., McAbee, Landis, & Burke, 2017; LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011; Chapter 2). These studies can be considered the mainstream scientific people analytics literature as a search for "people analytics" on Web of Science or Google Scholar will result in these studies (see Marler & Boudreau, 2017). However, the focus of this stream of research seems more *meta*, discussing the *what* and *how* of people analytics rather than its application or empirical evidence of its value. For instance, a recurring

topic is how to manage people analytics in practice, with scholars discussing the setup of the department, the required individual and organizational capabilities, and the delivery of people analytics projects (e.g., Andersen, 2017; Baesens, de Winne, & Sels, 2017; Levenson & Fink, 2017; Minbaeva, 2017b; Van der Togt & Rasmussen, 2017; Schiemann et al., 2017; Simón & Ferreiro, 2017). Fewer studies in this stream discuss actual applications of people analytics and those that do are mostly limited to high-level case study information (e.g., Kryscynski et al., 2017; Rasmussen & Ulrich, 2015; Van der Laken, Bakk, Giagkoulas, Van Leeuwen, & Bongenaar, 2017). In general, the stream is nearly void of empirical investigations, let alone applications of advanced analytics (e.g., text mining, predictive modelling, deep learning). Paradoxically, the mainstream people analytics literature consists mostly of *meta-research*, discussing but not demonstrating what people analytics is or what it brings to the table.

7.3.1.3 Data Mining and Decision-Support Systems

Third, there is a large scholarly community exploring applications of people analytics, but residing mostly outside of the HRM domain and refraining from use of the popular terminology. For instance, scholars have explored data mining algorithms and decision-support systems within HRM, mostly for selection purposes, but also in light of compensation, development, performance management, and retention (see Strohmeier & Piazza, 2013). These publications are highly technical and focused specifically on the data mining process, the predictive modeling process, and/or the decision-support quality. The theoretical implications, the strategic value, and the practical and ethical feasibility of the people analytics applications are discussed to a lesser extent (e.g., Al-Radaideh, & Nagi, 2012; Chien & Chen, 2008; Dursun & Karsak, 2010; Jantan, Hamdan, & Othman, 2010; Saradhi & Palshikar, 2011; Valle, Varas, & Ruz, 2012). Additionally, these studies are published almost exclusively outside of the (HR) management domain and do not use the popular management terminology (e.g., people analytics). However, this line of research very closely embodies what I would consider people analytics. This "*prospering new field of data mining research […] provides ample insights in how to generate advanced information and decision support within the HR domain*" (Strohmeier & Piazza, 2013, p. 40), thus exploring how information technology and predictive modelling allow for data-driven decisions on HRM topics (e.g., Davenport & Harris, 2007; Marler & Boudreau, 2017).

Unfortunately, such studies are infrequently conducted by HRM researchers or published in management and psychology journals. In light of Wright and Boswell's (2002) typology of HRM research, I have only encountered several studies focusing at the individual level of analysis and on a single practice, again in the selection space. For instance, a few scholars have adopted the data mining mindset and are applying machine learning to automatically evaluate jobs and match jobs and applicants (e.g., Kobayashi, Mol, Berkers, Kismihok, & Den Hartog, 2017). Similarly, scholars within recruitment and selection are considering the use of more advanced social network data and analysis, though still far off from creating automated decision-support systems (Caers & Castelyns, 2011; Kluemper & Rosen, 2009; Kluemper, Rosen, & Mossholder, 2012; Roth et al., 2016; Van Iddekinge, Lanivich, Roth, & Junco, 2016). When it comes to terminology, these HRM

scholars seem to regard the novel statistical modelling procedures as a natural evolution of their fields and do not refer to people analytics, even though their studies fit the definition closely.

7.3.1.4 Ambiguity

Overall, there are divergent streams of research related to people analytics. This may be the reason behind some of the ambiguity surrounding the topic. For instance, the traditional strategic HRM scholar imagines large quantitative survey studies linking HRM interventions and behavioral data to performance outcomes when thinking of people analytics. In contrast, micro-level HRM researchers may not be familiar with the term people analytics even though they work on novel, complex data analytics projects on a regular basis. At the same time, scholars outside of the social sciences are predicting employee behaviors with highly complex, unstructured data using black-box algorithms in machine learning pipelines, but not labelling it people analytics. Finally, the average HRM professional in practice will think of HR controlling, reporting, and dashboards when hearing the words people analytics, but is unaware of the potential value and pitfalls of more advanced data uses. An improved understanding of what people analytics and related concepts precisely entail, what they require of the data (e.g., volume, quality, causality), and what they can, and cannot do, seem prerequisites for people analytics to really take off in the future.

7.3.2 Bridges through People Analytics

Despite the ambiguity and slow development, the stream of people analytics brings new perspectives to science and practice. With its different purpose, people analytics has the potential to bridge the worlds of science and practice. Moreover, the complexity of the HRM issues people analytics seeks to solve could bridge different disciplines within these worlds.

7.3.2.1 Bridges between Science and Practice

Many authors in the field of people analytics have suggested that a large, problematic gap exists between research and practice (Minbaeva, 2017a, 2017b; Rasmussen & Ulrich, 2015; Simón & Ferreiro, 2017; Van den Heuvel & Bondarouk, 2017). Paradoxically, the worlds of HRM science and practice are increasingly collaborating under the banner of people analytics. For instance, practitioners and scholars have teamed up to disseminate information and knowledge across the science-practice border (e.g., Rasmussen & Ulrich, 2015; Chapter 3), to conduct applied empirical research with scientific value (e.g., Chapter 6; Kryscynski et al., 2017; Simón & Ferreiro, 2017; Van de Voorde, Paauwe, & Van Veldhoven, 2010), and to host PhD projects, academic conferences, and educational programs. As an *applied* or *design science*, taking the middle ground between descriptive theory and actual application (Van Aken, 2004, p. 225), the beauty is that people analytics research often comes with direct tangible benefits for both worlds. On the one hand, people analytics may provide strategic information for the organizations under study whereas, on the other hand, people analytics is a means to explore new HRM theories or to confirm their practical value. The organizations often

already have the necessary context and data – or a convenient sample at least – whereas the scholars often have the resources and capabilities to conduct a rigorous analysis.

Chapter 6 illustrates these dual benefits of people analytics. In Chapter 6, I demonstrate one way in which organizations can leverage the value of the longitudinal information they already store in their HR information system (HRIS). As a scholar, I had the necessary means (e.g., time, objectivity, access to literature) to come up with theory-based hypotheses, to identify and collect the relevant data, to transform them into the needed format, and to conduct sophisticated statistical analyses. However, I could not have performed my research without the longitudinal information that the two cooperating multinationals provided on an enormous sample of graduate trainees, or without the knowledge that their HRM professionals provided in identifying relevant data, interpreting data patterns, and considering their implications. In terms of practical value, the survival analysis of Chapter 6 quantifies to what extent the organizations were capable of retaining their graduate trainees and how several HRM practices affected this process. The analysis provided relevant insights into complex longitudinal processes and facilitated evidence for informed decision-making regarding several HRM policies and practices. In terms of the scientific value, in particular, the longitudinal, context-dependent effects of short-term assignment were an important finding. A conventional HRM research setup would not as easily have generated such dual benefits – illustrated by the lack of scientific knowledge on these novel types of assignments.

7.3.2.2 Bridges between Disciplines

Additionally, people analytics has the potential to form bridges between functional disciplines in both scientific and practical settings. On the one hand, people analytics teams work on a wide variety of issues within the HRM domain. Projects may explore recruitment and selection, training and development, career and succession planning, performance management and rewards, absenteeism, effective leadership, diversity and inclusion, effective teamwork, employee health and safety, culture change, communication networks, strategic workforce planning, and many more. This diversity of projects requires a diversity of knowledge, mostly related to HRM, organizational behavior, psychology, and other social sciences, but also some knowledge of labor legislation. Professionals with these kind of functional backgrounds have historically been present in the HRM domain – both in practice and in science.

On the other hand, people analytics projects call for more unusual expertise fields. Every project can require specific data sources, research designs, statistical analyses, legal considerations, and business implications. Take, for instance, the implementation of a decision-support system (i.e., predictive model) for the selection of successful job candidates. Its development and implementation will require knowledge of: how candidate success should be measured; what predictors could be important; how predictors should be measured; what and where data could be available; how data should be interpreted; which methods could be applied; how models and results should be interpreted; what possible HRM actions could be taken; what legal barriers and implications could be; what IT infrastructures could be used; how results and implications should be communicated; et cetera. People analytics teams therefore commonly include

professionals with diverse backgrounds. Common backgrounds include the HRM and psychology backgrounds that have historically been present, but also backgrounds in statistics, methodology, psychometrics, econometrics, physics, computer science and other quantitative fields. Moreover, in order to bring their projects to a success, people analytics teams will likely draw on the expert knowledge of professionals in fields such as information technology, communication, legal, and/or change management. This cross-disciplinary nature of applied research such as people analytics thus has the potential to decrease the borders between functional disciplines in both science and practice.

7.3.3 Privacy, Compliance, and Ethical Issues

Privacy can be defined as "*a natural right of free choice concerning interaction and communication […] fundamentally linked to the individual's sense of self, disclosure of self to others and his or her right to exert some level of control over that process*" (Simms, 1994, p. 316). People analytics may introduce privacy issues in many ways, including the data that is processed, the control employees have over their data, and the free choice experienced in the work place. In this context, ethics would refer to what is good and bad practice from a standpoint of moral duty and obligation when organizations collect, analyze, and act upon HRM data. The next section discusses people analytics specifically in light of data privacy, legal boundaries, biases, and corporate social responsibility and free choice.

7.3.3.1 Data Privacy

Technological advancements continue to change organizational capabilities to collect, store, and analyze workforce data and this forces us to rethink the concept of privacy (Angrave et al., 2016; Bassi, 2011; Martin & Freeman, 2003). For the HRM function, data privacy used to involve questions such as "*At what team size can we use the average engagement score without causing privacy infringements?*" or "*How long do we retain exit interview data?*" In contrast, considerably more detailed information on employees' behaviors and cognitions can be processed on an almost continuous basis these days. For instance, via people analytics, data collected with active monitoring systems[17] help organizations to improve the accuracy of their performance measurement, increasing productivity and reducing operating costs (Holt, Lang, & Sutton, 2016). However, such systems seem in conflict with employees' right to solitude and their freedom from being watched or listened to as they work (Martin & Freeman, 2003) and are perceived as unethical and unpleasant, affecting employees' health and morale (Ball, 2010; Faletta, 2014; Holt et al., 2016; Martin & Freeman, 2003; Sánchez Abril, Levin, & Del Riego, 2012). Does the business value such monitoring systems bring justify their implementation? One could question whether business value remains when a more long-term and balanced perspective is taken, considering the implications for employee attraction, well-being, and retention. These can be difficult considerations, requiring elaborate research and piloting.

[17] Continuous collection, storage, analysis, and reporting of data on employees' activities related to, for instance, presence, e-mail, browsing, or performance behaviors.

Faletta (2014) asked American HRM professionals which of 21 data sources would be appropriate for use in people analytics. While some were considered appropriate from an ethical perspective (e.g., performance ratings, demographic data, 360-degree feedback), particularly novel data sources were considered problematic: data of e-mail and video surveillance, performance and behavioral monitoring, and social media profiles and messages. At first thought, these seem extreme, overly intrusive data that are not and will not be used for decision-making. However, in reality, several organizations already collect such data (e.g., Hoffmann, Hartman, & Rowe, 2003; Roth et al., 2016) and they probably hold high predictive value for relevant business outcomes. Hence, it is not inconceivable that future organizations will find ways to use these data for personnel-related decisions – legally or illegally. Should they be allowed to? If not, who is going to monitor them? What if the data are used for mutually beneficial goals – to prevent problems or accidents? These and other questions deserve more detailed discussion by scholars, practitioners, and governments – preferably together.

7.3.3.2 Legal Boundaries

Although HRM professionals should always ensure that they operate within the boundaries of the law, legal compliance does not seem sufficient when it comes to people analytics. Frequently, legal systems are unprepared to defend employees' privacy against the potential invasions via the increasingly rigorous data collection systems (Boudreau, 2014; Ciocchetti, 2011; Sánchez Abril et al., 2012). Initiatives such as the General Data Protection Regulation in the European Union somewhat restore the power balance, holding organizations and their HRM departments accountable to inform employees what, why, and how personal data is processed and stored. The rights to access, correct, and erase their information is returned to employees (GDPR, 2016). However, such regulation may not always exist and, even if it does, data usage may be unethical, regardless of its legality.

For instance, should organizations use all personnel data for which they have employee consent? One could argue that there are cases where the power imbalance between employers and employees negates the validity of consent. For instance, employees may be asked to sign written elaborate declarations or complex agreements as part of their employment, without being fully aware of what they consent to. Moreover, employees may feel pressured to provide consent in fear of losing their job, losing face, or peer pressure. Relatedly, employees may be incentivized to provide consent because of the perks associated with doing so, without fully comprehending the consequences. For instance, employees may share access to personal behavioral data in exchange for mobile devices, wellness, or mobility benefits, in which case these direct benefits may bias their perception and judgement. In such cases, data usage may not be ethically responsible, regardless of the legal boundaries, and HRM departments in general and people analytics specialists in specific should take the responsibility to champion the privacy and the interests of their employees.

7.3.3.3 Automating Historic Biases

While ethics can be considered an important factor in any data analytics project, it is particularly so in people analytics projects. HRM decisions have profound implications in an imbalanced relationship, whereas the data within the HRM field often suffer from inherent biases. This becomes particularly clear when exploring applications of predictive analytics in the HRM domain.

For example, imagine that we want to implement a decision-support system to improve the efficiency of our organization's selection process. A primary goal of such a system could be to minimize the human time (both of our organizational agents and of the potential candidates) wasted on obvious mismatches between candidates and job positions. Under the hood, a decision-support system in a selection setting could estimate a likelihood (i.e., prediction) for each candidate that he/she makes it through the selection process successfully. Recruiters would then only have to interview the candidates that are most likely to be successful, and save valuable time for both themselves and for less *probable* candidates. In this way, an artificially intelligent system that reviews candidate information and recommends top candidates could considerably decrease the human workload and thereby the total cost of the selection process.

For legal compliance as well as ethical considerations, we would not want such a decision-support system to be biased towards any majority or minority group. Should we therefore exclude demographic and socio-economic factors from our predictive model? What about the academic achievements of candidates, the university they attended, or their performance on our selection tests? Some of those are scientifically validated predictors of future job performance (e.g., Hunter & Schmidt, 1998). However, they also relate to demographic and socio-economic factors and would therefore introduce bias (e.g., Hough, Oswald, & Ployhart, 2001; Pyburn, Ployhart, & Kravitz, 2008; Roth & Bobko, 2000). Do we include or exclude these selection data in our model?

Maybe the simplest solution would be to include all information, to normalize our system's predictions within groups afterwards (e.g., gender), and to invite the top candidates per group for follow-up interviews. However, which groups do we consider? Do we only normalize for gender and nationality, or also for age and social class? What about combinations of these characteristics? Moreover, if we normalize across all groups and invite the best candidate within each, we might end up conducting more interviews than in the original scenario. Should we thus account for the proportional representation of each of these groups in the whole labor population? As you notice, both the decision-support system and the subject get complicated quickly.

Even more problematic is that any predictive decision-support system in HRM is likely biased from the moment of conception. HRM data is frequently infested with human biases as bias was present in the historic processes that generated the data. For instance, the recruiters in our example may have historically favored candidates with a certain profile (e.g., red hair). After training our decision-support system (i.e., predictive model) on these historic data, it will recognize and copy the pattern that candidates with red hair (or with correlated features, such as a Northwest European nationality) are more likely successful. The system thus learns to recommend those individuals as the top candidates.

While this issue could be prevented by training the model on more objective operationalization of candidate success, most HRM data will include its own specific biases. For example, data on performance ratings will include not only the historic preferences of recruiters (i.e., only hired employees received ratings), but also the biases of supervisors and other assessors in the performance evaluation processes. Similar and other biases may occur in data regarding promotions, training courses, talent assessments, or compensation. If we use these data to train our models and systems, we would effectively automate our historic biases. Such issues greatly hinder the implementation of (predictive) people analytics without causing compliance and ethical issues.

7.3.3.4 Corporate Social Responsibility versus Free Choice

Corporate social responsibility also needs to be discussed in light of people analytics. People analytics could allow HRM departments to work on social responsibility agendas in many ways. For instance, people analytics can help to demonstrate what causes or prevents (un)ethical behavior among employees, to what extent HRM policies and practices are biased, to what extent they affect work-life balance, or how employees can be stimulated to make decisions that benefit their health and well-being. Regarding the latter case, a great practical example comes from Google's people analytics team. They uncovered that employees could be stimulated to eat more healthy snacks by color-coding snack containers, and that smaller cafeteria plate sizes could prevent overconsumption and food loss (ABC News, 2013). However, one faces difficult ethical dilemmas in this situation. Is it organizations' responsibility to nudge employees towards good behavior? Who determines what *good* entails? Should employees be made aware of these nudges? What do we consider an acceptable tradeoff between free choice and societal benefits?

When we consider the potential of predictive analytics in this light, the discussion gets even more complicated. For instance, imagine that organizations could predict work accidents based on historic HRM information, should they be forbidden, allowed, or required to do so? What about health issues, such as stress and burnout? What would be an acceptable accuracy for such models? How do we feel about false positive and false negatives? Could they use individual-level information if that resulted in benefits for employees?

In conclusion, analytics in the HRM domain quickly encounters issues related to privacy, compliance, and ethics. In bringing (predictive) analytics into the HRM domain, we should be careful not to copy and automate the historic biases present in HRM processes and data. The imbalance in the employment relationship puts the responsibility in the hands of organizational agents. The general message is that what can be done with people analytics may differ from what should be done from a corporate social responsibility perspective. The spread of people analytics depends on our collective ability to harness its power ethically and responsibility, to go beyond the legal requirements and champion both the privacy as well as the interests of employees and the wider society. A balanced approach to people analytics – with benefits beyond financial gain for the organization – will be needed to make people analytics accepted by society, and not just another management tool.

7.3.4 Optimizing HRM through Machine Learning

In essence, everything that happens in an organization, including HRM, has the potential to represent a learning experience. Whether we are dealing with recruitment and selection, with training and development, with rewards and performance, or with talent management and retention – the behavior of our employees can inform us to what extent our HRM processes are successful, or not. Here, people analytics helps us to improve the ways in which we measure and monitor these processes and their outcomes; to discern patterns in the large amounts of data we collect; and to actually learn by the numbers and improve our HRM decisions. The wider field of machine learning is particularly experienced with learning through data and has much to offer the HRM domain and people analytics. The next section discusses the value of cross-validation and the exploration-exploitation tradeoff.

7.3.4.1 Generalization via Cross-Validation

In many applied domains, such as HRM and people analytics, achieving accurate predictions is often a primary goal of research initiatives (Yarkoni & Westfall, 2017). For instance, we might want to examine to what extent applicants' characteristics predict whether they will be high-performing employees. However, conventional HRM research rarely verifies that the explanatory models they propose are capable of predicting the outcomes they are modeling. Moreover, from a statistical standpoint, it is rarely true that the model which best explains the sampled data at hand will provide the best predictions for outcomes in the real-world (Shmeuli, 2010; Yarkoni & Westfall, 2017). Too often, our HRM models will be overfitting the process at hand – mistaking sample-specific noise for relevant patterns – and will therefore not generalize well to new observations (Yarkoni & Westfall, 2017).

Machine learning scholars understand the importance of evaluating the predictive power of models and commonly do so by cross-validation: a family of techniques that involve training and testing models on different subsets of the sampled data (Breiman, 2001; Browne, 2000; Friedman et al., 2001). Following the standard procedure, we would train our statistical model on a random part of our dataset, and then assess (i.e., *test*) how accurate this model predicts the outcomes in the other part of our dataset. Although the information of the second, test sample goes to waste in this simplified example (i.e., does not help to train the model), smart approaches such as k-fold cross-validation effectively recycle training and testing data in order to leverage all information.

Cross-validation is rarely used to assess model performance in conventional management and psychology research. Nevertheless, the practice has deep roots in the field, for instance, in the form of classical replication research (Yarkoni & Westfall, 2017, p. 1110). Cross-validation techniques can, to some extent, assure that our HRM models not only fit the patterns in our current sample well, but also generalize to a wider context. It provides quantitative information on how well our model explains and predicts outcomes in- and out-of-sample. On the one hand, such cross-validation is important in preventing the reproduction crises faced in related domains (Open Science Collaboration, 2015), where models that were regarded as good explanations in an initial sample fail to accurately explain and predict the same outcome in future samples. Cross-validation

provides a way to assess the real-world value of our HRM models through replication at little to no extra cost (Yarkoni & Westfall, 2017). On the other hand, cross-validation becomes increasingly important with the rise of algorithmic methods in the HRM domain (see Strohmeier & Piazza, 2013) which are capable of modeling complex interaction and non-linear effects, and are thus prone to overfitting (e.g., Breiman, 2001). In order to build accurate predictive models – estimating the likelihood that employees will perform and be retained, or the likelihood that HRM interventions will be successful in specific contexts, for specific employees (e.g., personalized HRM) – the implementation of machine learning techniques such as cross-validation is critical. In sum, cross-validation can help HRM scholars in building explanatory and predictive models that do not overfit the coincidental patterns in research samples, but rather generalize to the wider population, and thus have value for real-world applications.

7.3.4.2 Exploration-Exploitation Tradeoff

A second, related learning for HRM and people analytics involves the exploration-exploitation tradeoff. This tradeoff considers the competing needs to, on the one hand, acquire new knowledge and information (exploration) and, on the other hand, optimize decisions based on existing knowledge and information (exploitation). By focusing resources on exploration, one gains information on the payoff of different options but retains less time to benefit from these options. By focusing resources on exploitation, one gains direct benefits but may potentially overlook alternatives with a higher payoff, resulting in suboptimal benefits on the long term. Although the exploration-exploitation tradeoff has been discussed previously in relation to organizational learning and survival (e.g., Gupta, Smith, & Shalley, 2006; March, 1991), the rise of evidence-based HRM and people analytics emphasizes its importance.

The HRM function is inherently oriented towards exploitation, but may want to explore more. Indeed, some exploration is central to the HRM design phase as practitioners may consult stakeholders concerns, scientific papers, and organizational metrics when designing and implementing HRM policies and practices (Rousseau & Barends, 2011). On top of this, progressive HRM departments may even conduct formal pilot studies (i.e., people analytics) to validate that the implementation achieves the right outcomes. However, once these steps are completed, policies and practices often remain unchanged for as long as they (seem to) benefit the organization. The knowledge that an HRM policy or practice works is exploited whereas ongoing, organized exploration of alternatives and modifications is rarely conducted.

While this focus of knowledge exploitation may have been viable for the traditional management of personnel in organizations, the current speed of change and digitalization requires and allows for more systematic exploration. For instance, let us revisit the selection decision-support system discussed earlier, recommending job candidates based on their predicted likelihood of being a successful hire. Ultimately, the effectiveness of such a system depends on the continuous exploration of new information and data patterns. For instance, imagine that the skills and competencies that jobs require change over time. A system focused purely on exploiting an established (i.e., trained) model will

not learn this and will keep recommending job candidates that were originally successful, but may no longer be.

Some exploration may be introduced in the form of feedback loop, where the model is updated as candidates are processed and succeed or fail, and thus continuously learns by example. However, more rigorous learning through exploration could be incorporated. For instance, we could allow the system to recommend historically less successful candidates on purpose, every now and then: candidates that would normally have been rejected automatically by the system. As these unorthodox candidates flow into the later stages of the selection process (e.g., interview with a human recruiter), they are labelled as either success (hire) or failure (reject) and the system can be updated accordingly. This would allow the system to learn at a considerably faster rate, either updating its assumptions about the patterns that reflect successful hires or reaffirming its basis of knowledge in case of failure. Such exploration is widely deployable, also outside of decision-support systems, and used in many other domains. For instance, large tech companies optimize their services continuously through real-time experimentation. Similarly, marketing and pharmaceutical companies simultaneously explore and exploit what works best during marketing and clinical pilots. This exploration does not have to be random, but may also occur through organized, theory-based, experimental design. Translated to an HRM context, exploration could imply more consciously recruiting, hiring, training, rewarding, or promoting in ways that are different from the current procedures – different from what we currently believe to be effective.

On the bright side, incorporating exploration in HRM processes helps to identify patterns and other insights that would otherwise not have been uncovered. This holds great potential for the optimization of our HRM policies and practices, allowing us to base HRM decisions on observations and facts instead of on legacy assumptions. Although disadvantages exist on the short term (e.g., time, costs, bad hires), organizations would learn and benefit from the newly generated knowledge on the long term. On the dark side, there are implications of exploration in an employment situation. A decision-support system that recommends random candidates for interviews every now and then will already be difficult to sell, let alone one that consciously recommends predicted misfits for learning purposes. Such exploration is likely in conflict with short-term business goals, employer branding, candidate interests, and potentially even legal boundaries. Moreover, governments, societies, organizations, managers, HRM departments, employee councils, and employees themselves are probably not yet ready for such exploration in terms of their mindset. However, in my eyes, a better balance between exploitation and exploration is the only way for predictive analytics to achieve its full potential in the functional HRM domain. Therefore, scholars, practitioners, and governments need to consider what it means to (not) introduce machine learning to the HRM domain, with or without explorative elements.

7.3.5 Unclear Value and Integration

On conferences, in newspapers, and at universities, the prominent message is that people analytics has the potential to generate incredible value for organizations. However, from an evidence-based perspective, there is little foundation for such claims.

The business value of the insights generated by people analytics projects in practice has not been sufficiently established, quantified, or proven yet. To my knowledge, only three scientific studies have empirically examined the benefits of people analytics. One study indeed demonstrated that people analytics can benefit organizational performance, but only when an effective HRIS and the right incentives are in place (Aral et al., 2012). While the other two studies found a positive relationship between people analytics capabilities and performance, this involved the individual performance of HRM professionals (Kryscynski et al., 2017) and the strategic performance of HRM departments (Lawler & Boudreau, 2015). Hence, the scientific evidence for the claimed operational benefits of people analytics seems limited.

Similarly, voices in practice increasingly question the value of people analytics. For example, Andersen (2017) discussed the field's infancy, criticizing the overly optimistic claims of impact that go round. Rasmussen and Ulrich (2015) provokingly caution that people analytics may simply be a fad, pointing to the lack of "*analytics about analytics*" that could demonstrate its value (Rasmussen & Ulrich, 2015, p. 237). I understand that quantifying of the benefits of people analytics can be a challenge, as it is hard to quantify the value of accurate management information. Nevertheless, people analytics teams could more purposefully explore and monitor the business consequences after finishing a project or after HRM practices or policies are changed based on their recommendations. More evidence of how operational results are affected or of the ways in which HRM decision-making improved because of people analytics would help to substantiate the business case for people analytics.

Without evidence for its added value, I expect people analytics to disappear as a separate function in the future. Other professionals in the field share these expectations (see Andersen, 2017; Van den Heuvel & Bondarouk, 2017). Most probably, people analytics will be integrated in a centralized cross-functional analytics function that is responsible for organization-wide analytical initiatives, irrespective of discipline and focus area. On the bright side, there could be great efficiency gains in having one big analytics function instead of multiple teams dispersed across HRM, marketing, finance and operations, doing the same thing (Andersen, 2017). A centralized team will be better able to combine multiple data sources and approach business cases and opportunities from different perspectives. Moreover, a centralized team could help to overcome the boundaries and barriers which the HRM function faces with regard to advanced analytics (Angrave et al., 2016). On the dark side, if people analytics were to move to a centralized team, projects aimed at HRM processes could be overlooked. HRM-related projects would compete with other, potentially more business-relevant and impactful projects in other functional domains. Moreover, if the HRM department would no longer be actively involved in analytical initiatives, employee interests could be overlooked. The potential ethical implications hereof, I discussed earlier.

7.4 Implications

7.4.1 Implications for HRM Research

While this dissertation was largely problem-, practice-, and data-driven, and not centered on a specifically theoretical framework, there are several implications for HRM research and the way science is conducted therein.

7.4.1.1 Collaborations

First, there are many opportunities for collaborations between science and practice under the label of people analytics. Such collaborations have the potential to benefit the scientific field of HRM, the responsible scholars, the organizations and their employees, and even society as a whole. Contemporary organizations have vast, longitudinal datasets containing information about their employees and the way they are managed. More often than not, however, they lack the expertise to leverage the value of such data (Van der Togt & Rasmussen, 2017). Fortunately, scholars can help to identify a natural experiment in a training context (Van der Laken, 2017), to prevent the loss of information in case of multi-level issues (Chapter 3), to identify opportunities and limitations of social media for employees selection (Roth et al., 2016), to match applicants and vacancies via text mining (Kobayashi et al., 2017), and to explore employee retention as a survival problem (Chapter 6). In this sense, innovative collaborations between organizations and scholars can assure that the vast amounts of data contemporary organization collect produce knowledge and insights. With a balanced approach, people analytics projects may materialize benefits for the organization (more effective HRM), its employees (well-being and productivity), the scholars (data and publications), and society (innovation, labor participation, well-being, and productivity).

7.4.1.2 Alternative Research

Second, I want to resonate the need for a divergence from purely explanatory studies. In contemporary management research, the balance between (scientific) rigor and (practical) relevance is off, highly in favor of the rigor dimension (Van Aken, 2004, p. 223). While emphasis on local problem-solving has been present in the form of Action Research (Eden & Huckham, 1996), in collaborative research (Rynes et al., 2001), and in mode 2 knowledge production (Gibbons et al., 1994), the last decades of management research have focused on explanatory, theory-driven research (Van Aken, 2004). People analytics has the potential to reintroduce a focus on practical relevance.

Similarly, Yarkoni and Westfall (2017) argue that a redistribution of energies over explanatory and predictive studies may benefit psychological science and bridge the gap between scientific study and real-world application (p. 1114-1118). Currently, there seems to be a "*lack of understanding […] of the difference between building sound explanatory models versus creating powerful predictive models, as well as confusing explanatory power with predictive power*" (Shmueli, 2010, p. 289). While it may not be directly obvious, predictive modeling actually serves many valuable scientific functions: it helps to explore causal mechanisms in contemporary, large datasets; develop and optimize new measurement instruments; test, compare, and improve current theories;

quantify the predictability of phenomena; et cetera (Shmueli, 2010; Shmueli & Koppius, 2011; Yarkoni & Westfall, 2017). In the long run, HRM as a scientific field would benefit from a better balance between studies that aim to explore, explain, and predict HRM phenomena and prescribe HRM solutions.

A related implication is that the social sciences should be more open to novel and/or alternative methodology. A familiarity with machine learning concepts such as cross-validation and regularization[18] could help HRM researchers to improve the real-world value of their HRM models substantially (Yarkoni & Westfall, 2017, p. 1107). Even *black-box* algorithms, which may not seem attractive from the perspective of basic science, could be valuable in explanatory HRM research. Their predictive accuracy may be valuable in the early research stages, for instance, to impute missing values or for propensity scoring in quasi-experimental designs. The value of unsupervised techniques for the future of the HRM domain should also not be neglected. Data reduction techniques become increasingly important in light of the enormous volumes of data that are being collected through new sources (e.g., wearables, sensors, gamification; Chapter 3). Clustering techniques could help to identify different types of employees based on longitudinal or high-dimensional information of employees' behaviors, cognitions, or emotions. In all these cases, a general familiarity of HRM scholars with the requirements, the possibilities, the inner workings, and the pitfalls of non-conventional methods would facilitate collaboration with other disciplines and the identification of novel research opportunities.

7.4.1.3 Publication Issues

Third, the changes mentioned above (science-practice collaborations, alternative HRM research) are only viable if the scientific publication process correctly incentivizes researchers. Currently, manuscripts which follow a deductive cycle where theory-driven hypotheses are tested in a confirmatory way have much more publication potential and this discourages scholars to study anything else (e.g., Hambrick, 2007; Leung, 2011; Pratt, 2008; Woo et al., 2017). If left unchanged, this process will greatly hinder the growth of people analytics as a discipline, both in the scientific world as well as in practice. People analytics is often problem-focused instead of theory-driven whereas decisions made in the statistical modelling process (e.g., construct operationalization, data handling, chosen technique or algorithm) may introduce additional barriers for getting accepted for publication in contemporary management and psychology journals (e.g., Shmueli, 2010; Woo et al., 2017).

I foresee two scenarios in this regard. In one scenario, the scientific HRM community reviews its publication process to assure that machine learning and people analytics projects are not discouraged. Publishers could devote special issues or journals to science-practice collaborations, knowledge transfer, technological innovation, or business impact. Similarly, research institutions could support career patterns that facilitate people analytics research, rewarding science-practice partnerships,

[18] A process whereby the objective function of a statistical model is changed in order to prevent overfitting.

valorization, and highly contextualized research. In either case, we ensure that the opinions, thoughts, and considerations of HRM scholars are considered with regard to the latest technological developments in the HRM space. A less bright scenario, in my opinion, is the continuation of the current trend in the people analytics space. In that case, people analytics applications will be published mostly in non-management scientific outlets (e.g., Expert Systems with Applications), semi-scientific management outlets (e.g., Harvard Business Review), and practitioner conferences (e.g., Wharton People Conference, Predictive Analytics World, UNLEASH). Here, it is possible that, instead of HRM scholars, the private parties behind successful technology initiatives become the thought leaders and driving forces that determine the future of HRM.

7.4.1.4 Expatriate Management Research

Fourth and final, this dissertation provides several implications for research on expatriate management. Chapter 4 and 5 demonstrated that international assignment and expatriate management may have impact along multiple dimensions. While the impact on retention, performance, and careers can be measured relatively easily in practice using HRIS data (see Chapter 6), the impact on the local community, on the family, and on well-being is harder to examine and quantify. Therefore, it is important that scholars study these non-work outcomes and promote a balanced perspective.

Chapter 5 also demonstrates that expatriate management scholars should pay attention to details when it comes to describing the study's variables, its sample, and its context. One can think of the home and host countries, the type of assignment, or the implemented mobility practices. Without this information, it is harder to culminate evidence for the effectiveness of global mobility support, and determine which effects are sample-specific and which generalize more broadly. For instance, Chapter 6 provides a first exploration of the implications of short-term international assignments as an alternative to traditional expatriation. At the same time, Chapter 6 demonstrates how survival analysis can help scholars in quantifying the long-term effects of expatriation. A more elaborate discussion of the scientific implications can be found in the discussion sections of Chapters 4, 5, and 6.

7.4.2 Implications for Practice

This dissertation also had several implications for practice.

7.4.2.1 Skill Requirements

In order to implement people analytics effectively, organizations will first need people analytics professionals with the right knowledge and skills. Such professionals need to be able to identify and scope a business problem, define the right research questions, collect the correct data, perform the appropriate statistical analyses, and communicate the results in an accessible and convincing manner. Moreover, they will need to establish and maintain a network of supportive stakeholders across the organizational hierarchy, businesses, and functions to deliver their projects (Andersen, 2017; Marler & Boudreau, 2017).

Some of these skills have traditionally not resided in the HRM function (Andersen, 2017; Green, 2017; Ulrich & Dulebohn, 2015). HRM professionals are often praised for their interpersonal skills, but their knowledge of business operations, quantitative methodology, and advanced analytics is usually less developed. On top of this, the HRM talents who have the right capabilities often move to work in other fields (Andersen, 2017). While some scholars are hopeful and observe that a quantitative mindset is developing within the HRM function (Van der Togt & Rasmussen, 2017), others grimly conclude that the function is not yet ready for analytics (Angrave et al., 2016). Either way, effective implementation of people analytics requires different capabilities than traditionally present in the HRM function. Depending on the ambition of the organization, contemporary HRM departments may choose to develop these capabilities internally, to bring them in from other parts of the organization (Andersen, 2017), or to team up with external parties (Kryscynski et al., 2017; Van der Togt & Rasmussen, 2017).

7.4.2.2 No Perfect Data

Second, people analytics is worth only as much as the data to which it is applied. The *garbage in, garbage out* principle should be clear by now. Data quality issues affect analysis conclusions and thus the quality thereof. Decision-making based on unreliable or invalid data can lead to decisions that result in the exact opposite of what was desired.

For that matter, organizations completely new to HRM data and people analytics are in a luxury position. They can closely consider what HRM and employee information is of strategic importance and, thus, what their ideal HRIS looks like (Andersen, 2017). With what interval should employee turnover be registered and the headcount updated? What information needs to be stored on the onboarding process or the exit interview procedure? What do we need to know about our employees' training and developmental activities? Additionally, these organizations could consult strategic HRM literature to build their employee survey from scratch. There is a plethora of research examining the psychological factors of work, how these can be operationalized, and how they influence business and employee outcomes (e.g., Van Veldhoven, Prins, Van der Laken, & Dijkstra, 2015).

Most organizations will already collect and store HRM data structurally. On the one hand, these organizations should continuously assess and improve the quality of their HRM data. One important element is clarity regarding the validity and reliability of measurements: what do our HRM data points actually represent and how stable are they. Organizations could look at the underlying factor structure of their employee surveys, the rater interreliabilities in the selection or evaluation processes, the stability of performance or potential ratings, or the amount of errors on the demographic data in their HRIS. Where issues arise, it could be worth to change the collection process or the data definition. However, this touches on the earlier discussed exploration-exploitation tradeoff: to what extent do we improve the current employee surveys and HRIS (exploration) or continue to analyze the longitudinal data collected in the current, potentially suboptimal system (exploitation)?

On the other hand, organizations should start piloting people analytics initiatives as soon as data quality reaches an acceptable level. Chapter 6 demonstrated the value of the

data that many contemporary organizations already possess in their HRIS, allowing the analysis of patterns over several years and a quantification of long-term impact. However, the data issues encountered in the HRIS in Chapter 6 also illustrate the challenges contemporary people analytics teams may still face. My overall conclusion would be that perfect data does not exist and that people analytics can already result in considerable insights based on the HRM data collected in standard HRIS, complemented with ad hoc additional data collection.

7.4.2.3 People Analytics Culture

Third, organizations are advised to create a culture where analytics is fully embedded. In the best-case scenario, any HRM initiative is accompanied by an analytical strategy including testable research questions, data collection before, during, and after the intervention, a clear analysis procedure, and continued monitoring after implementation. Although this strategy might not be viable for every minor policy change, it is definitely necessary for large scale projects. Crucial would be that not only the people analytics project team is analytically skilled, but that the whole HRM community knows what is (not) possible so that they can ask the right questions and spot opportunities on a daily basis.

7.4.2.4 Expatriate Management

Fourth and final, Chapters 4 through 6 discuss detailed practical implications for expatriate management in organizations. An additional implication for practice would be that organizations should aim for evidence-based expatriate management and assess to what extent their global mobility policies are achieving their objectives. Here, analysis using clever proxies and data stored in HRIS can already result in many interesting insights. For instance, if expatriation is used mainly for managerial development, the rate of change in performance and potential evaluations of managers over time could be analyzed in light of whether they were internationally assigned are not. Similarly, longitudinal changes in job level and salary grades could be assessed to inspect the implications of expatriation for careers. Here, organizations should compare the implications of different forms of expatriation (e.g., long-term, short-term, commuting, hardship) to estimate their cost-effectiveness. In all cases, organizations should also test whether employees are more or less likely to leave during or after assignment. Not only does this hint to what extent investment in global mobility is cost-effective, but it may also display whether well-being, adjustment, repatriation, or career issues exist. Overall, the HRIS data collected in many contemporary organizations already provides a good foundation to make expatriate management more evidence-based.

7.5 Future Research

Based on my dissertation, I have several general recommendations for future research on people analytics in general, and people analytics applied to expatriate management research.

7.5.1 People Analytics

Future research on people analytics should take three different perspectives. First, future research should explore the strategic value of people analytics and evidence-based HRM. On a macro-level, they could compare HRM departments and organizations with differing levels of people analytics maturity and evidence-based mindsets to explore to what extent this influences HRM efficiency and effectiveness, HRM's credibility as rated by other disciplines, and business, HRM, and operational outcomes. I do foresee that a quantification of the benefits of people analytics on this level could be difficult due to inter-organizational differences. Hence, on a micro-level, scholars could examine how people analytics affects the decision-making process of individuals. For instance, to what extent does people analytics make decision-makers more confident, faster, or unanimous in their HRM decisions, or to what extent does people analytics increase their capabilities to predict the impact of their decisions. On a case-level and more focused on impact, scholars and practitioners could aim to quantify how changes in HRM policies and practices made in light of people analytics projects have affected operational and financial results.

Second, scholars should explore the implications of new data sources. Modern technology is producing richer data which may hold value for a wide variety of HRM research topics. For instance, text mining applied to exit interviews could help to uncover motives for employee turnover. Characteristics of employees' social networks could be predictive for their long-term career success. Sentiment analysis of messages on enterprise communication tools could help to gauge employee engagement. Sensors may help to explore work and meeting patterns and optimize work floor designs. "Smart" work badges may help to map team cohesion and inclusion. E-mail software could be consulted to explore the health implications of overwork measured by after-hours emails. The possibilities seem endless and, as a result, many of the aforementioned analyses are already pioneered in practice. More scholarly involvement is needed to provide new and strong theoretical perspectives and to define the legal and ethical boundaries and responsibilities when it comes to these data.

Third, HRM scholars should get involved in research on machine learning within the HRM domain in order to explore its strategic and practical implications. Machine learning will allow for more personalized HRM. Training courses, career steps, or mentors could be recommended to employees on an individual level, based on their current needs and interests and those of historic employees similar to them. Are such practices I-deals 2.0? How do they affect the psychological contract?

Machine learning will also cause a wave of automation, which is already visible in the systems supporting HRM professionals in their HRM decisions. Here, scholars could examine in what HRM process (e.g., selection, remuneration, career planning) and in what stages of those processes (e.g., first screening, candidate ranking, employee selection), a decision-support system would be more or less valuable. Alternatively, scholars could explore how different parameter settings of decision-support systems or operationalizations of the outcome variables prevent or introduce bias; how quickly

models would update following changes in the underlying relationships; or what acceptable levels of predictive performance metrics are for different HRM processes.

Moreover, scholarly attention is required on the ethics surrounding machine learning and decision-support systems in general. Where are the ethical boundaries in exploration through experiments with HRM practices? What are the implications of (not) including conscious or random learning experiences in predictive systems? What do we consider an optimal tradeoff between exploration and exploitation in light of a long-term balanced perspective? HRM scholars should get on this bandwagon and make sure that the developments related to machine learning in HRM contexts follow a balanced approach.

7.5.2 Expatriate Management

The field of expatriate management research may struggle with the inherent characteristics of expatriation. Expatriates are hard to come by and can differ quite considerably from one another in terms of their personal characteristics (e.g., host/home country, nationality, personality) and their assignment and organizational context (e.g., duration, type, hardship, mobility support). Fortunately, I see two avenues by which a people analytics approach may help expatriate management research overcome these challenges.

First, technological advances may help to circumvent sample size issues by facilitating within-person research. For instance, experience-sampling methods (ESM) gather intensive repeated assessments with brief intervals and study durations (Beal, 2015). Such study designs have the potential to capture the expatriate experience on a much more granular level compared to repeated or cross-sectional surveys while being relatively simple to implement with the current technological developments. ESM may help to capture a wide range of expatriate experiences, close to the moment of occurrence, as they are experienced in real-life (Beal, 2015). Concrete examples of how ESM could improve our knowledge of the expatriation process lie in an investigation of how home and host country social networks change over time, how the perceived organizational support and psychological contract change during the expatriation cycle, or in uncovering the true shape of the adjustment curve.

Alternatively, text mining methodology and sentiment analysis can generate rich data regardless of the sample size. For instance, scholars could mine interview data to explore what themes and concepts are considered to contribute to or impair expatriate experiences. Here, scholars could combine old and new interview data to compare what topics are mentioned in relation to international assignment and whether these have changed due to advances in communication technology or the rise of alternative assignments and dual-career families. On a comparative level, the textual content of the global mobility policies of different companies could be processed and analyzed to explore where differences exist and what these imply for assignment success.

Moreover, social network analysis may be interesting in light of expatriation and sample size. Here, scholars could explore to what extent the social networks of assignees change during and after the assignment. Rich information could be gathered in relation to the home and host country networks, and both in the work and personal atmospheres.

Such social network analyses are not only interesting for adjustment, retention, and performance outcomes, but also for knowledge transfer. Social network analysis can demonstrate how information is disseminated between home and host countries or between parent and subsidiary companies and whether intracompany communication channels improve because of expatriation.

Second, collaborating with large multinationals may solve sample size issues. With their large expatriate populations scholars could test, for instance, whether assignments characteristics (e.g., home-host country combinations, duration, benefits) influence work, life, and family outcomes, keeping other personal and organizational context characteristics stable. Moreover, these larger companies are the perfect context to explore and experiment in what ways the expatriate experience abroad may be improved, for instance, by assigning some expatriates mentors or buddies, or by initiating communities. Preferably, researchers could look for natural experiments, where the HRM or mobility policies have changed over time, or have changed for specific group of assignees but not the other. Finally, multinationals usually have large, longitudinal HRIS and survey databases that are relatively rich in information compared to the small, convenience samples common in scientific expatriate research. Here, scholars could trade-off some of their theoretically founded measures in return for larger data volume.

7.6 Conclusion

The current speed of technological development is rapidly changing the way in which we organize and manage employees. Fortunately, these developments come with improved capabilities to collect and analyze data about the perceptions and behaviors of employees and how these are influenced by HRM policies and practices. While it seems that both HRM research and practice have been slow to adopt analytics, the right skill- and mindset are developing, if not with some assistance from other domains. This dissertation demonstrated how people analytics can help HRM to become more evidence-based, illustrated among others in application to expatriate management. I propose that people analytics and the adoption of machine learning principles will bring more automated and personalized HRM with continuous improvement through exploration and experimentation. At the very least, the HRM function should retain an advisory seat at the analytics table in order to champion employee interests and advocate a balanced approach to machine learning initiatives. In the best case scenario, HRM scholars and HRM professionals will explore and lead this rise of people analytics.

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9.3 Explanation of time-varying covariate format of Chapter 6

Several variables in Chapter 6 were *time-varying* in the sense that respondents could have multiple measurements. For instance, employees received their first performance and potential ratings after some time on the job and these ratings were updated annually. Additionally, employees were assigned and repatriated from STIA and thereby accumulated international experience and had changing mobility status. Not accounting for these time dependencies causes serious implications, most importantly *immortal time*[19]. For example, graduate recruits with a performance rating inherently survive until the start of their (first) performance evaluation and, retrospectively, appear immortal as none leaves the organization. If this immortal time is not accounted for, models incorrectly estimate strong positive effects of time-varying covariates.

Immortal time is prevented by encoding time-dependent covariates with a (start, stop] format (Fox & Weisberg, 2011; Therenau, Crowson, & Atkinson, 2017). Here, a record is duplicated whenever a covariate changes. The original record is right-censored at the moment of change, after all, there is no observation of what would have happened if the change had not occurred. The duplicate record is left-censored at the moment of change, after all, there is no observation of what would have happened had the change occurred earlier. The duplicate record ends as usual: either at another change of a covariate, at the end of the observational timeframe, or at turnover. Figure 9.3.1 displays this transformation on simplified example data. Despite appearances, this transformation does not cause multicollinearity because the survival analysis techniques are programmed to only use a single record per subject, depending on the point in time (Therenau et al., 2017).

ID	Hiring	Turnover	STIA
1	01-01-2017	-	-
2	01-01-2017	-	01-03-2017
3	01-01-2017	01-04-2017	-
4	01-01-2017	01-04-2017	01-03-2017

Note: observation period ends 01-07-2017

ID	t(start)	t(end)	Turnover	Status
1	0	181	FALSE	Local
2.1	0	58	FALSE	Local
2.2	59	181	FALSE	STIA
3	0	90	TRUE	Local
4.1	0	58	FALSE	Local
4.2	59	90	TRUE	STIA

Note: t = time in days

Figure 9.3.1: A simplified example of the transformation to a time-varying covariates format.

[19] Suissa, S. (2007). Immortal time bias in pharmacoepidemiology. *American Journal of Epidemiology*, *167*(4), 492-499.

10 Executive summary

This dissertation explored how the Human Resource Management (HRM) function is becoming more evidence-based through data analytics. The past decade has witnessed a tremendous rise in public interest in *people analytics* – the use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions involving personnel (see Chapter 1). However, scientific publication networks suggest that the use and added value of analytics is less widespread for the HRM function than for other functional management domains (e.g., marketing, IT, supply chain), at least in terms of the volume and diversity of academic research (Chapter 2).

Arguably, a paradigm change is needed for HRM to fully leverage the business value of the complex data generated through modern technology. Historically, HRM scholars have focused on the development and confirmation of overall management theories through explanatory research (versus exploratory or predictive research). Additionally, complex, quantitative analyses have historically not been present in HRM research and practice. Fortunately, people analytics may facilitate a paradigm change as it involves problem- and solution-oriented research with as its main purpose the provision of local, applied insights in order to optimize HRM activities. In such research projects, the methodology is usually fit to the purpose and the data at hand (Chapters 3 and 7).

In order to demonstrate how people analytics facilitates evidence-based HRM, this dissertation specifically explored its application to expatriate management. It sought to define and quantify expatriate success and uncover the impact of and best practices related to the social support provided during the expatriation cycle (Chapters 4 and 5). Additionally, this dissertation demonstrated how to quantify the local impact of, for instance, short-term international assignment for talent retention (Chapter 6). The dissertation concludes with a discussion on people analytics and the future of HRM research and practice, covering topics related to ethics, privacy, machine learning, cross-functional collaborations, and their implications (Chapter 7).

11 Management samenvatting

Dit proefschrift onderzocht in welke mate de Human Resource Management (HRM) functie gebaat is bij de opkomst van *analytics* in het managen van personeel op basis van data-gedreven inzichten en bewijsvoering. De afgelopen tien jaar is er in meerdere mate aandacht besteed aan zogenaamde *people analytics* – het gebruik van data, statistische en kwantitatieve analyse, exploratieve en voorspellende modellen, en *evidence-based* management om beslissingen over personeel te nemen (Hoofdstuk 1). Echter, netwerk analyses op de wetenschappelijke literatuur over analytics in relatie tot organisatieprestaties laten zien dat de HRM functie achter lijkt te lopen op andere management domeinen (bijv. marketing, IT, en logistiek), in ieder geval wat betreft de wetenschappenlijke aandacht voor het onderwerp (Hoofdstuk 2).

Een paradigmaverandering is nodig voordat de HRM functie de volledige waarde leert te halen uit de complexe data die wordt gegenereerd met moderne technologie. Historisch gezien focussen HRM wetenschappers zich op verklarend onderzoek (versus exploratief of predictief onderzoek) waarbij ze algemene management theorieën trachten te formuleren. Daarnaast hebben complexe, kwantitatieve analyses historisch gezien geen deel uit gemaakt van het HRM domein, noch in de wetenschap, noch in de praktijk. *People analytics* kan de paradigmaverandering hier versnellen, aangezien het probleem- en oplossing-gedreven onderzoek omvat met als hoofddoel om toegepaste, bedrijfsrelevante inzichten te genereren om het dagelijks personeelsmanagement te verbeteren. Hierbij wordt de onderzoeksmethodologie veelal aangepast op basis van het onderzoeksdoel en de beschikbare data (Hoofdstukken 3 en 7).

Om aan te tonen hoe people analytics bijdraagt aan *evidence-based* HRM is in dit proefschrift specifiek onderzocht hoe analytics kan worden toegepast met betrekking tot de internationale uitzendingen van personeelsleden. Zo is gekeken hoe het succes van zulke uitzendingen kan worden gedefinieerd en hoe dit gemeten kan worden. Vervolgens kon middels het kwalitatief en kwantitatief samenvatten van eerder onderzoek worden vaststellen wat de te verwachten impact is van diverse vormen van (organisatorische) ondersteuning gedurende zulke uitzendingen (Hoofdstukken 4 en 5). Tevens is specifiek onderzocht hoe de impact van, onder andere, kortlopende internationale opdrachten op de retentie van talenten kan worden gekwantificeerd (Hoofdstuk 6). Uiteindelijk blikt het discussiehoofdstuk van deze dissertatie terug op de mogelijke meerwaarde van people analytics en de toekomst van HRM onderzoek en praktijk. De dissertatie sluit af met een bespreking van people analytics vraagstukken omtrent ethiek, privacy, *machine learning*, multi-disciplinaire samenwerkingen, en verdere implicaties (Hoofdstuk 7).

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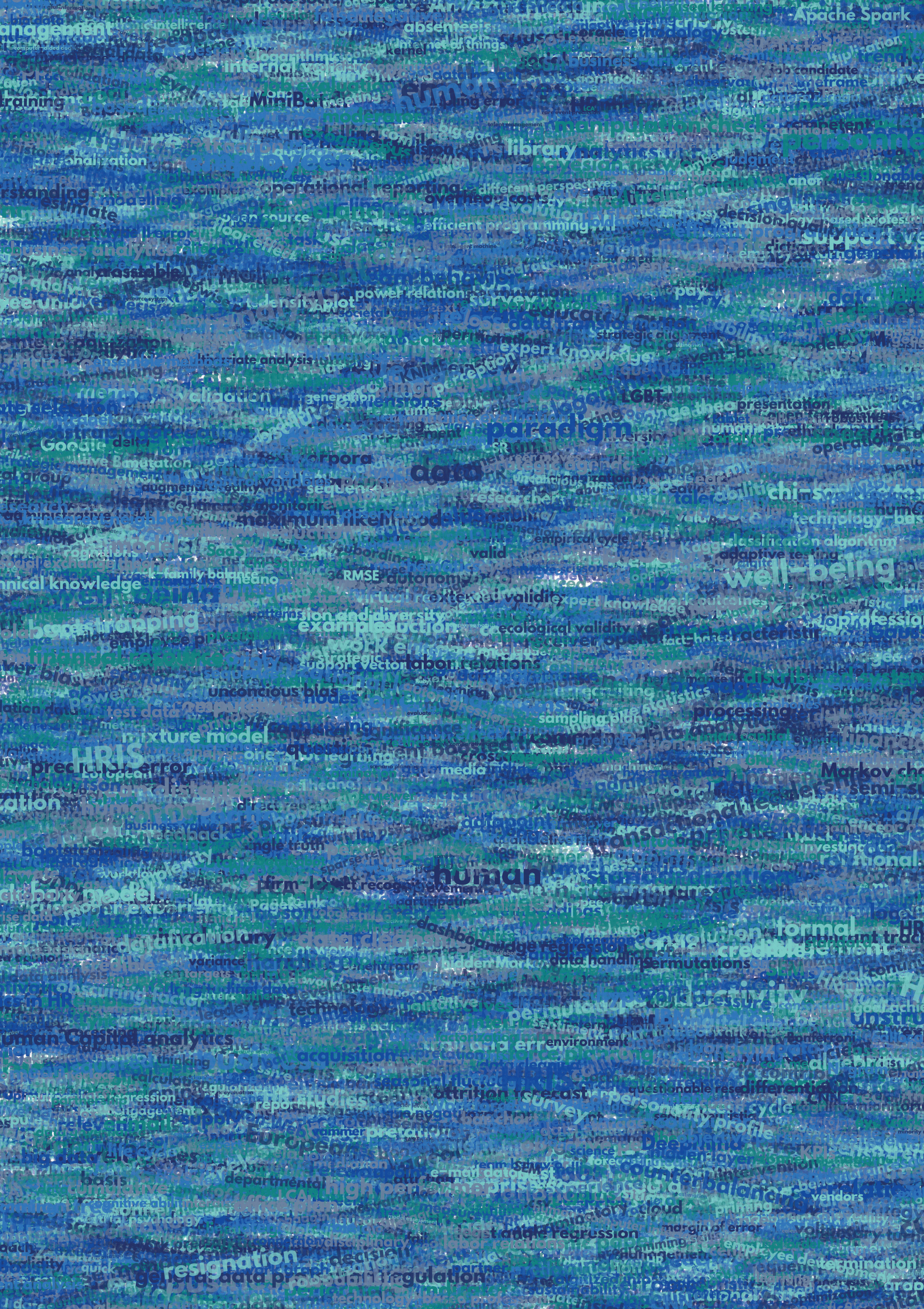
Apache Spark
paradigm
data
well-being
human
HRIS
mixture model
labor relations
unconcious bias
maximum likelihood
power relations
expert knowledge
ecological validity
external validity
permutations
data handling
resignation
least angle regression
margin of error
attrition forecast
department
acquisition
environment
Human Capital analytics
Markov
LGBT
presentation
adaptive testing
multivariate analysis
overhead costs
operational reporting
efficient programming
library
personalization
MiniBatch
training
sampling plan
processing
direct report
single truth
technology
variance
vendors
basis
RMSE
valid
empirical cycle
classification algorithm