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LITERATURE REVIEW

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The dark sides of people analytics: reviewing the perils for organisations and employees

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ABSTRACT
Technological advances in the field of artificial intelligence (AI) are heralding a new era of analytics and data-driven decision-making. Organisations increasingly rely on people analytics to optimise human resource management practices in areas such as recruitment, performance evaluation, personnel development, health and retention management. Recent progress in the field of AI and ever-increasing volumes of digital data have raised expectations and contributed to a very positive image of people analytics. However, transferring and applying the efficiency-driven logic of analytics to manage humans carries numerous risks, challenges, and ethical implications. Based on a theorising review our paper analyses perils that can emerge from the use of people analytics. By disclosing the underlying assumptions of people analytics and offering a perspective on current and future technological advancements, we identify six perils and discuss their implications for organisations and employees. Then, we illustrate how these perils may aggravate with increasing analytical power of people analytics, and we suggest directions for future research. Our theorising review contributes to information system research at the intersection of analytics, artificial intelligence, and human-algorithmic management.

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1. Introduction

People analytics has the potential to transform the way organisations identify, develop, manage and control their workforce (Chamorro-Premuzic et al., 2017; Huselid, 2018). The term "people analytics" does not refer to a technology, but to a novel, quantitative, evidence-based, and data-driven approach to manage the workforce (Gal et al., 2020; McAfee et al., 2012). This approach aims to raise the efficiency of core human resource (HR) functions such as workforce planning, recruiting, development and training, as well as to optimise employees' and the organiation's performance (Bodie et al., 2016; Gal et al., 2017; Leonardi & Contractor, 2018; Tursunbayeva et al., 2018). Consequently, it is hardly surprising that organisations worldwide are increasingly deploying people analytics to analyse and link data on human behaviour, social relationships and employee characteristics to internal or external business information (Fernandez & Gallardo-Gallardo, 2020; Leonardi & Contractor, 2018).

Data-driven decision-making in this new era of people analytics has been facilitated by recent advancements of learning algorithms in the field of artificial intelligence (AI) (Faraj et al., 2018; von Krogh, 2018). The term 'learning algorithms' refers to a set of technologies able to adaptively interpret and learn from large data sets to perform human-like cognitive tasks (Benbya et al., 2020; Faraj et al., 2018; Mayer et al., 2020). Learning algorithms are becoming more and more prevalent in people analytics to predict output values from given input data, (Cappelli, 2019; van den Heuvel & Bondarouk, 2017). Moreover, these algorithms are increasingly able to reliably perform and potentially even outperform humans in a growing number of tasks (Faraj et al., 2018; Strich et al., 2021). The new analytical power of learning algorithms also enables organisations to process, combine and analyse the ever-increasing volumes of digital data, as well as to automatically identify patterns in structured and unstructured data (Brynjolfsson & Mitchell, 2017; von Krogh, 2018).

The rapid progress in the field of AI has raised organisational expectations and reinforced widely held assumptions on the power, transparency, accuracy and objectivity of learning algorithms, contributing to a very positive image of people analytics among researchers and practitioners (Gal et al., 2017; Greasley & Thomas, 2020; King, 2016; Marler & Boudreau, 2017; Tursunbayeva et al., 2019). For example, people analytics has been described as "critical to any organisation's success" (Boudreau, 2017, p. 1), stamped as the "new kid on the block" (Baesens et al., 2017, p. 20), labelled as "game changer for the future of HR" (van der Togt & Rasmussen, 2017, p. 131), and assuring the HR function "the potential

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to become one of the leaders in analytics" (Davenport, 2019, April 18, p. 1). These high hopes tend to build on three underlying assumptions. Firstly, decision-making based on learning algorithms is often considered superior and more reliable than human decision-making (Kryscynski et al., 2018; Leicht-Deobald et al., 2019; Martin-Rios et al., 2017). Algorithms' high processing capacity enables rapid analysis of large data volumes to identify statistical patterns and correlations (Gal et al., 2017; Newman et al., 2020). Thereby, algorithms are thought to increase fairness, transparency and objectivity (Jabagi et al., 2020; Martin-Rios et al., 2017; Sharma & Sharma, 2017). Secondly, people analytics is believed to predict, modify, and manage current and future human behaviour, particularly through systematically analysing and exploring historical data (Chamorro-Premuzic et al., 2017; Gal et al., 2017; Isson & Harriott, 2016). The assumption is that current and future behaviour can be explained and predicted from the analysis of past actions and their consequences (Sivathanu & Pillai, 2019; N. Wang & Katsamakas, 2019). Thirdly, people analytics is considered to be able to streamline self-aware, subjective human beings, just as it is able to optimise inanimate objects, processes and material resources (Gal et al., 2017; Nocker & Sena, 2019). With humans as immediate subject of analysis, people analytics aims to influence and optimise their behaviour through quantitatively analysing their conduct and their digital traces (Gal et al., 2020; Leicht-Deobald et al., 2019).

However, these assumptions can be problematic because they contribute to a very positive perception of people analytics without attention to potential risks, which might entail serious consequences for organisations and employees. For instance, to treat employees similarly to quantifiable data objects, rather than as genuine fully-fleshed human beings could entail a conceptual category error (Gal et al., 2017, 2020; Leicht-Deobald et al., 2019). People analytics based on recent technological advances in the field of AI could potentially underestimate human complexity, be more invasive, and have more serious consequences for employees than other forms of business analytics, as in analysing goods, money flows, key financial figures, etc. (Gal et al., 2020; King, 2016; Leicht-Deobald et al., 2019). Consequently, the underlying assumptions of people analytics' role, capabilities and promises among researchers and practitioners hold particular ethical and moral challenges. This can guide organisations and managers towards a strong or even unbalanced reliance on people analytics and result in severe perils.

Our paper seeks to unpack the inherent assumptions and expectations that underlie the use of people analytics. In so doing, we portray a nuanced and critical picture of its potential ramifications and implications. Further, we seek to problematise increasing technological advancement's role in the context of people analytics and to shed light on the critical aspects of algorithm-based decision-making in this context by answering the following research question:

> *What are the perils of people analytics and what are their potential negative implications for organisations and employees?*

This paper aims to review the potential perils emerging from largely unchallenged assumptions and organisational expectations associated with the use of learning algorithms in people analytics and to discuss the negative effects these algorithms have on decision-making, management, and human capabilities. We are expanding the limited body of knowledge in the people analytics field to include a critical analysis of the potential threats and resulting implications, particularly focussing on the pitfalls associated with using more sophisticated technologies (Bodie et al., 2016; Gal et al., 2017; Leicht-Deobald et al., 2019). Advancing academic work in this field intends to help researchers and practitioners to adopt an informed and realistic approach to people analytics.

Our paper offers two major theoretical contributions: First, we propose a novel maturity level to account for the recent technological advancements and the emergence of learning algorithms and AI in the analytics' field. By systematically reviewing the literature on people analytics and highlighting future research avenues, we extend the field of people analytics and contribute to a more nuanced and balanced understanding of people analytics. Secondly, we theorise the emergence of potential perils for organisations and employees and how they may aggravate with increasing technological progress. Thereby, our paper is among the first to carve out the peculiarities of people analytics and explain why overlooking these peculiarities could bear significant risks and lead to the emergence of perils for organisations and employees. This way, we contribute to the growing body of literature on the dark sides of technologies, analytics and AI.

In the remainder of the paper, we first conduct a systematic literature review to map the current field of people analytics. Subsequently, we describe the themes which have emerged from the literature review by describing the opportunities, barriers, and maturity of people analytics and highlight the associated idiosyncrasies and risks identified in prior research. In the following, we depict how the technological advancements and the nascent introduction of learning algorithms and AI have the potential to take people analytics to a new level. Concluding, we conceptualise six perils of people analytics, which can arise from the use of people analytics and the technological advancements. Thereby, we scrutinise their undesirable, unintended consequences for organisations and employees. Finally, we illustrate how and why the negative implications of these perils can escalate as the analytical power of people analytics increases.

2. Reviewing the current state of the people analytics literature

Over the last few years, the literature on people analytics has grown rapidly. Nevertheless, conceptual papers that offer typologies to categorise different people analytics practices and areas of application (e.g., Angrave et al., 2016; Dulebohn & Johnson, 2013; Ulrich & Dulebohn, 2015) as well as literature reviews that integrate the mainly practitioner-oriented and limited academic literature (e.g., Ekawati, 2019; Marler & Boudreau, 2017; Tursunbayeva et al., 2019) still dominate this nascent literature. Similarly prevalent are case studies that focus on the consequences of particular people analytics practices (e.g., Martin-Rios et al., 2017; Schiemann et al., 2018; Simón & Ferreiro, 2018). Thus, empirical research in this field is still scarce and rigorous quantitative or qualitative research examining the consequences of people analytics are lacking (e.g., Greasley & Thomas, 2020; van den Heuvel & Bondarouk, 2017). In sum, the literature on people analytics is still in its early stages (Angrave et al., 2016; Huselid, 2018; Marler & Boudreau, 2017; Minbaeva, 2018) and it predominantly paints an optimistic portrait of how people analytics could help organisations flourish (e.g., Green, 2017; McIver et al., 2018; Nienaber & Sewdass, 2016; Simón & Ferreiro, 2018).

Prior integrative literature reviews have primarily focused on what people analytics is and how it operates (Falletta & Combs, 2020; Marler & Boudreau, 2017), how it should be implemented (Angrave et al., 2016; Boudreau & Cascio, 2017; Fernandez & Gallardo-Gallardo, 2020), the value proposition it offers (Tursunbayeva et al., 2018; van den Heuvel & Bondarouk, 2017; Werkhoven, 2017a), and how it can influence performance (Aral et al., 2012; Peeters et al., 2020; Sharma & Sharma, 2017). Most of the prior integrating literature took a functional approach to people analytics (Peeters et al., 2020; van der Togt & Rasmussen, 2017), converging on how it can help improve firms' effectiveness, but paying less attention to this approach's ethical challenges, possible consequences, and risks (for exceptions, see conceptual papers, Gal et al., 2020; Leicht-Deobald et al., 2019). Therefore, we seek to advance the literature on people analytics by systematically mapping the field, identifying common themes in the literature, and consolidating what we know and do not know about the field (Paré et al., 2016; Rowe, 2014).

2.1. Methodology

We conducted this systematic literature review following Paré et al.'s (2016) guidelines. Thus, we (1) developed a review plan, (2) defined and applied a literature search strategy, (3) refined our findings in terms of contribution to our research objective, (4) assessed the remaining studies' quality with respect to the information systems field, (5) identified relevant themes, and (6) synthesised our findings (Paré et al., 2016). Following the systematic literature review, we elaborate on the recent technological advances in the field of people analytics and carve out the resulting potential perils for organisations and employees. (Figure 1) provides an overview of our search procedure.

Firstly, in developing a review plan, we were guided by the rationale of identifying critical knowledge gaps, as well as missing and neglected themes in extant research (Okoli, 2015; Paré et al., 2016; Rowe, 2014; Webster & Watson, 2002). In the review process, we combined descriptive and exploratory aspects, openly mapped the people analytics field based on the systematic literature review, and categorised emerging themes, patterns and trends found in the literature.

Secondly, we formulated a systematic literature search strategy to identify publications related to the use of people analytics (see Table 1 for our detailed inclusion criteria). In sum, we searched four databases, namely Business Source Premier, Scopus and PsychInfo accessed via Ebsco host, and then additionally, Web of Science. We chose these databases, because they are among the most often used ones in systematic literature reviews (Aguinis et al., 2020; Hiebl, 2021) as well as to cover literature on people analytics from related disciplines such as Information Systems, Organisational Behaviour or Human Resource Management. Further, we searched the AISEL Electronic Library to also include premier IS conference proceedings that are considered important indicators for emerging trends as well as to include the most recent academic discussions and advancements. Finally, we conducted a backward and forward search to uncover relevant articles not identified in our prior literature search (Webster & Watson, 2002).

Thirdly, we defined our exclusion criteria and removed duplicates (see Table 2, E.I). Next, we manually screened abstracts and other relevant paragraphs considering their contribution to our literature search goal. We removed papers that only mentioned the search terms as an expression or in a general data analytics context without a clear focus on HR (E.II). Next, we excluded articles primarily geared towards the technical implementation of software, methods and algorithms (E.III). Further, we excluded

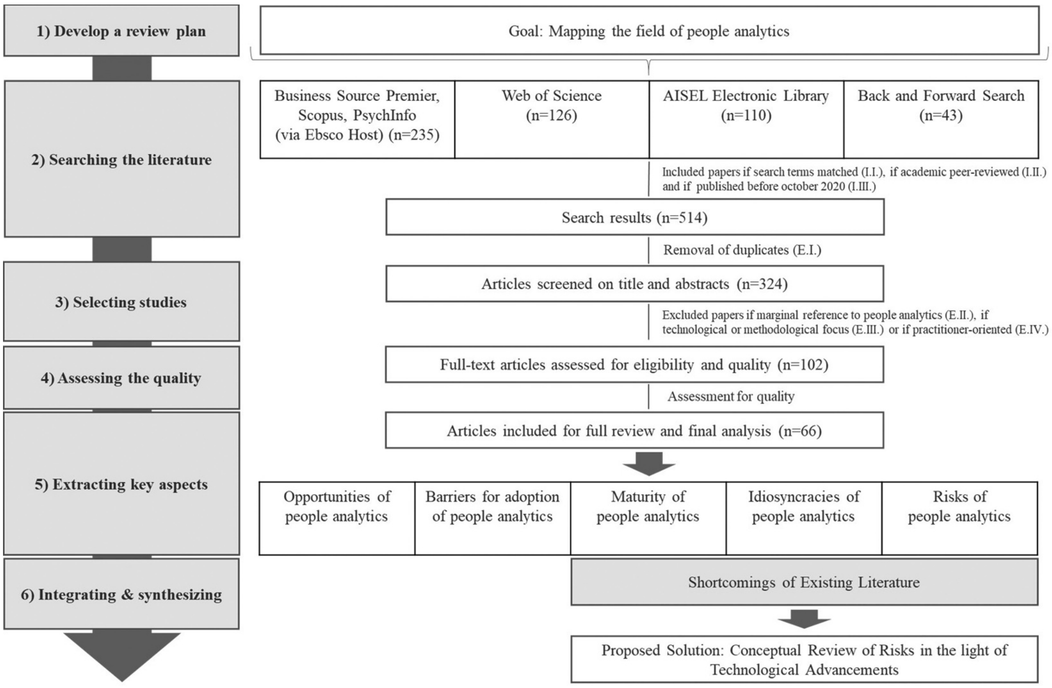

Figure 1. Overview of search procedure.

practitioner-orientated papers, such as those published in People & Strategy, Strategic HR Review, Harvard Business Review or Sloan Management Review (E.IV).

Fourthly, we assessed the articles' quality and eligibility. We included those published in ranked journals and the three most prominent IS conferences [European Conference on Information Systems (ECIS), Hawaii International Conference on System Sciences (HICSS), and International Conference on Information Systems (ICIS)]. Two of the authors independently coded the primary studies. In case of disagreement, they discussed the discrepancies until they reached consensus. Finally, we selected 66 papers for the final analysis of the study, i.e., slightly less than 20.4 % of the overall number of studies selected in the first round. Overall, 55 of the 66 papers had been published in or after 2017, thus confirming the rapid proliferation of people analytics literature in the last few years. Further, the majority of the studies (54 of 66) were published in disciplines other than IS, such as Business, Management and Accounting, as well as Organisational Behaviour and Human Resource Management.

2.2. Emerging themes from the people analytics literature

Fifthly, applying a theme-centred approach, we analysed the remaining studies to identify predominant themes in the people analytics literature (Leidner, 2018; Rowe, 2014; Webster & Watson, 2002). We inductively generated the themes of this review during the process of engaging with the body of literature (Locke et al., 2020), and then quantitatively coded the studies accordingly (Webster & Watson, 2002). We found that predominantly the studies focused on one or more of the following emergent themes, which are summarised in Table 3.

Table 1. Inclusion criteria.

Inclusion Criteria
I.I. Presence of terms and synonyms related to people analytics: "people analytics", "HR analytics", "personnel analytics", "administrative data analytics", "HCM analytics", "workforce analytics", "human capital analytics", "human capital workforce analytics", "human resource analytics", "workplace analytics", "talent analytics".
I.II. Academic peer-reviewed papers focusing on the adoption of people analytics (i.e., any form of data-driven decision-making in human resource management).
I. III. Relevant studies published in English before October 2020.

Table 2. Exclusion criteria.

Exclusion Criteria
We removed . . .
E.I. . . . duplicates
E.II. . . . studies with only marginal reference to people analytics
E. . . . III. studies restricted to the technical or methodological aspects of people analytics – for example, evaluation of machine learning models or data mining methods
E. . . . IV. practitioner-oriented articles primarily offering practical recommendations on how to implement people analytics

Table 3. Overview of emerging themes of people analytics literature.

Themes	Definition	Key Aspects	Total Nr of Studies	Sample Publications
Opportunities of people analytics	Opportunities refer to the promises, benefits and expectations of organisations regarding the use of people analytics	• diverse areas of application, such as recruitment, development, retention • improvement of performance and efficiency • improved work experience and job satisfaction	53	Aral et al., 2012; Kryscynski et al., 2018; Rasmussen & Ulrich, 2015; Tursunbayeva et al., 2018; van der Togt & Rasmussen, 2017
Barriers to adopting people analytics	Barriers describe the obstacles and reasons hindering or slowing the adoption of people analytics	• lack of analytical skills • lack of an integrated data basis • lack of collaboration with other functions • technical barriers	41	Angrave et al., 2016; Dahlbom et al., 2019; Fernandez & Gallardo-Gallardo, 2020; Marler & Boudreau, 2017; Minbaeva, 2018
Maturity of people analytics	Maturity refers to the analytical capacity of people analytics	• maturity levels of people analytics • descriptive, predictive and prescriptive people analytics • maturity of people analytics relatively low	40	Ben-Gal, 2019; Ekawati, 2019; King, 2016; Sivathanu & Pillai, 2019; van den Heuvel & Bondarouk, 2017;
Idiosyncrasies of people analytics	Idiosyncrasies relate to the particularities and distinctive characteristics of people analytics	• ethical and moral implications • invasiveness • consideration of human complexity • far-reaching consequences	13	Bodie et al., 2016; Falletta & Combs, 2020; Khan & Tang, 2017; Nocker & Sena, 2019; Schafheitle et al., 2019;
Risks of people analytics	Risks refer to likely sources of dangers of people analytics and their negative consequences for organisations and employees	• privacy and data protection concerns • surveillance and constant tracking • algorithmic biases	10	Calvard & Jeske, 2018; Gal et al., 2017; Gal et al., 2020; Leicht-Deobald et al., 2019; Newman et al., 2020

2.2.1. Theme 1: opportunities of people analytics

Scholars and practitioners alike have suggested that people analytics offers businesses great promise (Huselid, 2018; Rasmussen & Ulrich, 2017; Tursunbayeva et al., 2018). Consequently, the largest part of scholarly attention has gone to the opportunities people analytics offers. Overall, 53 studies have highlighted such opportunities, addressing the following three sub-themes: opportunities and business-oriented benefits, employee-oriented benefits, and assumptions underpinning people analytics.

A common thread in this theme is the potential people analytics has to transform the way organisations identify, develop and evaluate their talent (Chamorro-Premuzic et al., 2017; Fernandez & Gallardo-Gallardo, 2020; Martin-Rios et al., 2017). The underlying rationale of many studies seems to be the belief that people analytics can generate actionable insights for all stages of the employee life cycle to improve operational and strategic firm performance (Levenson, 2018; Minbaeva, 2018; L. Wang & Cotton, 2018). Several studies emphasise the diverse areas of application, such as workforce planning, onboarding, personnel development, performance-appraisal, diversity management and retention (Aral et al., 2012; Bekken, 2019; Frederiksen, 2017).

Other studies highlight the possible benefits of people analytics for employees by offering health-benefits and development opportunities for employees to extend their experience (e.g., Gal et al., 2020; Huselid, 2018; Tursunbayeva et al., 2018). Scholars have argued that people analytics can make "workers more efficient, more productive, happier, and more likely to be loyal to their employer" (Bodie et al., 2016, p. 23). Some studies even going as far as to state that "in ten years, no single decision within the HR domain will be made without a clear business case supported by statistical data" (van den Heuvel & Bondarouk, 2017, p. 169).

In sum, these promises seem to be fuelled by underlying assumptions: firstly, people analytics is more objective and less error-prone than human decision-making, and secondly, based on historical data, it is able to predict future human behaviour:

Regarding the ability to induce more objective, rational and bias-free decision-making (Claus, 2019; Marler & Boudreau, 2017; Tursunbayeva et al., 2019), people analytics endeavours to replace subjective human decision-making, because intuition, gut feeling, individual experience and unformalised know-how often stem from biased beliefs and are therefore not considered as valid, rigorous or trustworthy for assessing talent or creating HR policies (Gal et al., 2017; Greasley & Thomas, 2020; King, 2016). Drawing on large pools of quantitative data from a variety of sources, people analytics is said to deliver only a single, bias-free representation of the truth to decision-makers (Bodie et al., 2016; Gal et al., 2017).

Since algorithms are applied repeatedly and reliably, they can increase objectivity, transparency and fairness in the decision-making process (Gal et al., 2017; Jabagi et al., 2020; Newman et al., 2020).

As such, people analytics and algorithm-based decision-making are considered superior and less error-prone than human decision-making (Kryscynski et al., 2018; Leicht-Deobald et al., 2019), thus offering unprecedented organisational intelligence (Martin-Rios et al., 2017). Owing to their large processing capacity, algorithms can mine an immense depth and breadth of data to detect patterns and correlations, whereas human decision-makers can only handle a limited amount of input (Gal et al., 2017; Martin-Rios et al., 2017; Sharma & Sharma, 2017). People analytics' computational power and its underlying algorithms far exceed human cognitive resources in terms of speed, efficiency, and consistency (Gal et al., 2017; Jabagi et al., 2020; Kryscynski et al., 2018). As a result, people analytics is said to increase the quality of decisions and to support organisations in making more efficient, accurate and informed HR decisions (Bodie et al., 2016; Falletta & Combs, 2020).

Regarding the second assumption, people analytics is thought to be able to predict, modify and manage human behaviour (Chamorro-Premuzic et al., 2017; Gal et al., 2017; Isson & Harriott, 2016). The central claim is that making sense of past actions and their consequences enables decision-makers to explain current behaviour, diagnose and understand the underlying reasons, and predict future trends (Sivathanu & Pillai, 2019; N. Wang & Katsamakas, 2019). Thus, people analytics can gain insight from historical data or current data to understand past, current and future employee and business performance (Fernandez & Gallardo-Gallardo, 2020; King, 2016). High prediction accuracy allows managers to make rational, anticipatory decisions that were previously not possible, such as forecasting workforce resources and addressing emerging gaps in competences (Bhardwaj & Patnaik, 2019; Nienaber & Sewdass, 2016; Schiemann, 2018).

In all, very many studies highlight the potential promises and opportunies of people analytics. Rigorous empirical studies measuring such benefits with scrutiny are, however, rare (Kryscynski et al., 2018; Newman et al., 2020), and much of the evidence is still anecdotal (King, 2016; Schiemann et al., 2018). Future research could thus investigate the largely untested relationships that past literature disclosed.

2.2.2. Theme 2: barriers to adopting people analytics

In total, 41 of the 66 studies in our data set addressed the question of possible barriers to adopting people analytics. These studies suggest manifold underlying reasons for explaining why HR practitioners have been slow in adopting people analytics practices (e.g., Angrave et al., 2016; Marler & Boudreau, 2017; Vargas et al., 2018). We summarise the relevant studies here in three subthemes: lacking the required analytical capabilities, lacking a consistent, integrated data base and data analysis approach, and technical or software-related barriers.

One common theme emerging from these studies is that HR professionals often lack the required analytics capabilities (Angrave et al., 2016; Dahlbom et al., 2019; Kryscynski et al., 2018; Levenson, 2018). Because data do not speak for themselves, HR managers have to decide which questions to ask, how to interpret and make sense of the findings, put the results in perspective, and draw conclusions from the data (Boudreau & Cascio, 2017; Leicht-Deobald et al., 2019; Minbaeva, 2018). Traditionally, HR professionals not only lack the required analytical, technical, and methodological skills to perform such analysis; they also lack a data mindset (Andersen, 2017; Calvard & Jeske, 2018; Rasmussen & Ulrich, 2017). Thus, many HR employees are sceptical, ambivalent or reluctant, as they doubt whether humans can be reduced to numbers and wonder how they can use employees' data in an ethically legitimate way (Angrave et al., 2016; Greasley & Thomas, 2020; Kryscynski et al., 2018). Additionally, complying with legislation and data protection regulations while keeping people's trust, make it difficult for HR managers to process (non-anonymised) personnel data (van den Heuvel & Bondarouk, 2017).

Further, several studies stress that only a few firms have a unified, integrated and cleansed data basis and analytic approach (Lawler et al., 2004; Lismont et al., 2017; Minbaeva, 2018). This prevents merging employee data with data from other functional areas such as finance, sales, or production, and analysing it (Boudreau & Cascio, 2017; Kassick, 2019; Levenson & Fink, 2017). Silo mentalities in companies can also prevent HR professionals from combining HR data with data on other productivity and performance determinants, thus precluding HR from achieving meaningful objective performance outcomes (Bhardwaj & Patnaik, 2019; van der Togt & Rasmussen, 2017). Also, HR professionals tend to be situated in relatively peripheral positions in the organisational hierarchy (Angrave et al., 2016; Greasley & Thomas, 2020). Such a situation alongside the micro-political challenges HR departments face could further hamper collaboration with other units and prevent HR from obtaining top management's support for analytical efforts, or could limit them in implementing the people analytics project's recommendations in practice (King, 2016; van den Heuvel & Bondarouk, 2017).

Other studies that address this theme investigate the technical or software-related barriers hindering the adoption of (more) advanced forms of people analytics (Ben-Gal, 2019; Dahlbom et al., 2019; Vargas et al., 2018). Several studies stress that HR information systems are often limited to questions focused on operational reporting rather than providing the capacity HR departments need to perform statistical analysis (Andersen, 2017; Fernandez & Gallardo-Gallardo, 2020).

Overall, studies subsumed under this theme focus on human, data, and on technical barriers to adopting people analytics for putting a strong analytics strategy in place. Despite the wealth of research on this topic, future research could contribute by using multi-case studies or longitudinal research designs to empirically identify the barriers, determining how they evolve over time and how to overcome them.

2.2.3. Theme 3: maturity of people analytics

In all, 40 studies explicitly examined or at least commented on the current analytical maturity of people analytics. Within this topic, we identified two major sub-themes, referring to people analytics' low maturity, and to its different maturity levels and approaches.

One of this theme's dominant ideas is that analytical forecasting and decision support tools in this domain are still in their infancy compared to other corporate areas such as marketing, sales, production planning or finance (Chamorro-Premuzic et al., 2017; Marler & Boudreau, 2017; Schiemann, 2018). A large number of studies emphasise that the existing use of data analyses has hardly progressed beyond reactive, standardised, or demand-related historical reporting and rudimentary forecasts (Angrave et al., 2016; Lunsford & Phillips, 2018; van den Heuvel & Bondarouk, 2017). Consequently, most organisations are still struggling to move from basic operational reporting to more advanced forms of analytics (Boudreau & Cascio, 2017; Dahlbom et al., 2019; Minbaeva, 2017).

Beyond the consensus on people analytics' low maturity, we identified several studies that apply a widely used categorisation from the business analytics literature (Davenport et al., 2007; Delen & Demirkan, 2013), distinguishing three analytics maturity levels according to their analytical focus and capacity. The three levels are descriptive analytics, predictive analytics, and prescriptive analytics (Ekawati, 2019; Fernandez & Gallardo-Gallardo, 2020; King, 2016).

Descriptive analytics seeks to examine what occurred in the past and how this influences the present, by answering the question "What happened?" (Isson & Harriott, 2016; Lunsford & Phillips, 2018). It is based on standard statistical methods, such as correlation analysis, simple regressions, mean values and percent changes (Ekawati, 2019; Leicht-Deobald et al., 2019; Sivathanu & Pillai, 2019). It helps organisations to understand past and current business performance, to identify problem areas, needs for action, and business opportunities (Fernandez & Gallardo-Gallardo, 2020; Schafheitle et al., 2019). Descriptive people analytics is typically performed using the balanced scorecard and key performance indicators such as absenteeism rates (King, 2016; Leicht-Deobald et al., 2019).

Predictive analytics builds on identifying explanatory patterns (such as trends, relationships, preferences, clusters) from past or present events to forecast future business developments (Fernandez & Gallardo-Gallardo, 2020; Sivathanu & Pillai, 2019). The central question it answers is "What will happen and why?" (Isson & Harriott, 2016; King, 2016). To this end, it leverages statistical and mathematical methods such as advanced regression techniques, data mining, text mining, web mining, and forecast calculations (Ekawati, 2019; Sivathanu & Pillai, 2019; Ulrich & Dulebohn, 2015). Predictive analytics determines the probability that an event or possible development will occur, typically by providing a score that represents the likelihood of the event (Leicht-Deobald et al., 2019; Schafheitle et al., 2019). Thus, predictive analytics enables the forecasting of future employee behaviour and performance, such as predicting employee attrition or changes in levels of engagement. Therefore, it is often depicted as an early warning system (Kryscynski et al., 2018; Sivathanu & Pillai, 2019; van den Heuvel & Bondarouk, 2017).

Prescriptive analytics not only forecasts future development, but also recommends decisions and courses of action, based on an analysis of past data and alternative, future scenarios (Leicht-Deobald et al., 2019; Schafheitle et al., 2019). In so doing, it seeks to answer the question "What should be done?" and goes beyond merely predicting future outcomes (Isson & Harriott, 2016; Leicht-Deobald et al., 2019). In addition to the methods deployed by predictive analytics, prescriptive analytics uses solution-oriented simulation and scenario calculations as well as machine learning algorithms with the aim of developing decision proposals or, in extreme cases, implementing these decisions (Lunsford & Phillips, 2018; Sivathanu & Pillai, 2019). Prescriptive analytics can be used to optimise the efficiency of employees' behaviour or to model complex strategic HR decisions (Fernandez & Gallardo-Gallardo, 2020; Leicht-Deobald et al., 2019). At this stage, decision-making becomes a joint human-algorithm decision-making process (Burton et al., 2019; Schafheitle et al., 2019).

Finally, several studies stress that the three types of analytics offer increasing analytical power (Frederiksen, 2017; Leicht-Deobald et al., 2019). Among the empirical studies in this theme (Aral et al., 2012; Hicks, 2018; Schiemann et al., 2018), we find that most studies only examine the use of descriptive and predictive analytics techniques (e.g., Bekken, 2019; Chalutz, 2019; Dahlbom et al., 2019). However, recent technological advances in the context of people analytics illustrate the need to expand current research and emphasise the use of more advanced forms of people analytics.

2.2.4. Theme 4: idiosyncrasies of people analytics

Compared to the other themes, research on the idiosyncrasies and challenges of applying analytics to humans is limited. Overall, only 13 out of 66 identified studies examined or referred to idiosyncrasies and peculiarities of applying analytics to manage humans (e.g., Gal et al., 2017; Leicht-Deobald et al., 2019; Nocker & Sena, 2019; Schafheitle et al., 2019). The overall consensus of these studies is that trying to apply the logic of data-driven management from other parts of the organisation to manage the workforce entails several pitfalls due to four main idiosyncrasies of people analytics.

Firstly, compared to analytics applications in other business domains, applying analytics and algorithms in analysing, evaluating, controlling and managing employees invokes ethical and moral challenges with far-reaching implications (Falletta & Combs, 2020; Gal et al., 2017). For instance, in other areas, using business analytics to demonstrate business processes' inefficiency and then cutting costs on such a basis, is widely accepted and not frowned upon (Appelbaum et al., 2017; Khan & Tang, 2017). By contrast, similarly using people analytics to manage humans and their behaviour in an organisation, poses a range of ethical and moral questions that need careful consideration (Peeters et al., 2020; Schafheitle et al., 2019). Thus, treating employees as quantifiable data objects, rather than as cultural, sentient social human beings is ethically questionable (Gal et al., 2017, 2020; Leicht-Deobald et al., 2019). Applying algorithms to manage humans has potentially profound organisational, practical, societal, moral and ethical implications in workplaces that have yet to be studied and suitably addressed (Calvard & Jeske, 2018; Nocker & Sena, 2019; Peeters et al., 2020).

Secondly, human engagement can be too complex to be measured, evaluated and analysed in a data-driven way similar to other parts of the organisation (Gal et al., 2020; King, 2016). Because human behaviour is much more complex and much less predictable than that of machinery or other tangible assets, reducing complex human characteristics and behaviour for representation by data points and numbers is problematic (Gal et al., 2017; King, 2016; Newman et al., 2020). Therefore, directly transferring and extending analytics to organisational areas traditionally handled on the basis of human judgment and expertise, may fail to consider human complexity; moreover, significant misinterpretation, miscalculation, and costly strategic mistakes are likely (Falletta & Combs, 2020; King, 2016; Nocker & Sena, 2019).

Thirdly, compared to other forms of business analytics, people analytics is more invasive to employees, also in interfering with the individual's way of working and living in several ways (Bodie et al., 2016; Gal et al., 2017; Khan & Tang, 2017): The data collected for people analytics tend by their nature to be very sensitive, granular and personal. As such, the data allows organisations deep individual-target insight (and inter-reference) in employee's personal life, as well as in their psychological disposition (Falletta & Combs, 2020; Nocker & Sena, 2019; Schafheitle et al., 2019). By contrast, humans are not the immediate subject of analysis for most other forms of business analytics (e.g., in analysing goods, money flows, key financial figures, etc.), therefore, for the most part, employees are only marginally affected by analytics in other disciplines (Gal et al., 2017). Further, even compared to the wide use of personal data elsewhere, people analytics is different and more pervasive for two major reasons related to individuals' awareness of access to personal data and to their ability to withhold or withdraw personal information. Through extensive media coverage, most people are aware that their personal details, such as their private social media activities or their smart device usage is stored and transformed for further use (e.g., Fox & Moreland, 2015; Mai, 2016; Mantelero, 2016). In the organisational context, however, employees are less aware of the extent to which their employer harvests and evaluates their data (Bodie et al., 2016; Isson & Harriott, 2016; Khan & Tang, 2017). Also, in their private lives, people have the possibility of opting out, actively abstaining from using an internet platform, and sharing only information on aspects of their lives that they authorise (Nocker & Sena, 2019). By contrast, in the workplace context, due to their financial dependency in the employment relationship, employees might not have the opportunity to object to their data being evaluated or to stop their data being shared with external analytics providers (Peeters et al., 2020; Schafheitle et al., 2019; Simbeck, 2019). Together, these factors – processing personal and possibly sensitive data, as well as employees' inability to opt out and so escape these technologies' adverse effects – account for and reinforce the intrusive nature of people analytics (Falletta & Combs, 2020; Nocker & Sena, 2019; Schafheitle et al., 2019).

Finally, people analytics is more consequential for human beings than any other form of business analytics (Gal et al., 2017; Khan & Tang, 2017). With most business analytics applications, wrong decisions or inaccurate predictions can result in financial loss, but not in life-changing situations for employees

(Schafheitle et al., 2019). For instance, using analytics for organisational fleet management comprises activities such as evaluating and optimising the utilisation of vehicles (e.g., replacing high mileage vehicles with newer ones). Yet, the analogous use of people analytics to evaluate employees' workloads according to their performance and then filtering out underperforming or costly employees, would have a potentially life-altering impact on those ranked low in the assessment (Leicht-Deobald et al., 2019). Quite obviously, the cost of errors in such a situation is significantly higher in HR management than in other business settings, as evaluation and optimisation can determine employees' future career prospects, thus directly impacting not only their professional lives, but also their private sphere (Bodie et al., 2016; Falletta & Combs, 2020). Therefore, the risk of miscalculation and misinterpretation weighs more heavily and can lead to more fundamental and profound ethical and moral questions regarding people analytics decisions (Calvard & Jeske, 2018; Falletta & Combs, 2020; Gal et al., 2017).

In sum, the idiosyncacies outline above illustrate the danger of mindlessly applying logic from other business analytics areas to people analytics. Most studies in this theme outlined only one or two of these idiosyncratic aspects and none of them empirically investigated the possible effects. Following up on this explication and empirically analysing these peculiarities of people analytics and their potential consequences, future research could make an important contribution to this theme.

2.2.5. Theme 5: risks of people analytics

Compared to the preceding categories, the risks and negative implications of people analytics have attracted the fewest scholarly discussions (Angrave et al., 2016; Chamorro-Premuzic et al., 2017; Marler & Boudreau, 2017). Only 10 of the 66 studies examined or pointed towards potential drawbacks of people analytics (e.g., Calvard & Jeske, 2018; Newman et al., 2020; Schafheitle et al., 2019). Of these, only three studies explicitly investigated risks associated with people analytics (Gal et al., 2017, 2020; Leicht-Deobald et al., 2019), whereas the remaining six studies only pointed towards potential perils in their conclusions or in designating future research.

The majority of these studies raised privacy and data protection concerns that result from increasingly intrusive actions of people analytics (Hamilton & Sodeman, 2020; Peeters et al., 2020; Simbeck, 2019). These studies stress that employees face more and more invasive information collection, processing and dissemination as the people analytics boundaries are progressively extended from employees' work lives into their social and even physiological spaces. Such intrusion was found to evoke negative responses and resistance from employees and to hamper their commitment (Bodie et al., 2016; Khan & Tang, 2017).

Closely related to these privacy concerns, some studies explicitly addressed the issue of surveillance, constant tracking and algorithmic control of workers (Hamilton & Sodeman, 2020; Jabagi et al., 2020; Schafheitle et al., 2019). These studies stress that constant tracking, collecting and exploiting novel types of granular and sensitive data can foster feelings of being controlled, and can impede workers' autonomy, which often results in counterproductive behaviour (Hamilton & Sodeman, 2020; Jabagi et al., 2020; Leicht-Deobald et al., 2019). Particularly, extensively monitoring non-job-related behaviours could have detrimental consequences that affect employee perceptions negatively (Schafheitle et al., 2019).

Additionally, a number of studies pointed out the issue of implicit algorithmic bias resulting from poorly trained algorithms or inherent, yet subtle, human bias in the training data (e.g., Gal et al., 2017; Hamilton & Sodeman, 2020; Newman et al., 2020). Further, a handful of studies indicated that people analytics and the sometimes non-transparent functioning of algorithmic decision-making can produce a lack of algorithmic transparency (e.g., Gal et al., 2020; Schafheitle et al., 2019). Additionally, only a few studies have discussed how increasing datafication and nudging adversely affects the workplace on employees' virtue ethics (Gal et al., 2020) or how algorithm-based decision-making can impair employees' personal integrity (Leicht-Deobald et al., 2019). Similarly, the risks and detrimental effects of error variance and potential reductionism (Boudreau & Cascio, 2017; Gal et al., 2017) have also only limitedly been researched. Consequently, the papers we identified that deal with potential negative consequences of people analytics unequivocally call for more research on these risks (Calvard & Jeske, 2018; Gal et al., 2017, 2020; Tursunbayeva, 2019; Tursunbayeva et al., 2018; van den Heuvel & Bondarouk, 2017).

2.3. Synthesis of the literature

Finally, we synthesised our findings to map the field of people analytics, to identify underlying assumptions and to problematise the increasing technological advancements' role in the context of people analytics (Alvesson & Sandberg, 2011). Our literature review has demonstrated that a wealth of studies address the promises of and barriers to people analytics adoption, whereas the idiosyncrasies, the negative implications and associated risks have received little attention. At the same time, our literature review also shows that the majority of studies in this field concern themselves with a rather low level of people analytics' maturity, primarily investigating descriptive and predictive analytics. Thereby, current literature focuses on analytical approaches seeking to answer what has happened and what will happen, based on common statistical methods, such as simple regression models (Isson & Harriott, 2016; Leicht-Deobald et al., 2019). In practice, however, organisations increasingly begin to apply more advanced people analytics technologies, using learning algorithms and AI – even surpassing what is known as prescriptive analytics (e.g., Cappelli, 2019; Davenport, 2018, 2019, April 18).

Correspondingly, recent literature highlights the need to advance the field of people analytics by considering more advanced analytical methods and emerging technologies (e.g., Dahlbom et al., 2019; Davenport, 2019, April 18; van den Heuvel & Bondarouk, 2017). For instance, Dahlbom et al. (2019) emphasise that "new types of data and different algorithms used in AI and machine learning solutions utilized in HRA [Human Resource Analytics]" (p. 123) will transform the field of people analytics. Others highlight an upcoming shift „from automation to artificial intelligence“ (van den Heuvel & Bondarouk, 2017, p. 165) and that „automated learning and AI solutions will play an even greater role" (Schafheitle et al., 2019, p. 23) in the next few years. Furthermore, some researchers stress that AI and big data will revolutionise people analytics as these "new technologies, coupled with the near-ubiquitous digitization of work and work-related behaviors, has the potential to help organizations monitor, predict, and understand employee behaviors (and thoughts) at scale, like it has never been done before". (Chamorro-Premuzic & Bailie, 2020, p. 1). Similarily, Davenport (2018) underlines: "Today, firms might incorporate predictive or prescriptive analytics into existing offerings . . . [but] . . . AI takes this activity to the next level by providing increased automation and sophistication" (p. 76). Thus, scholars highlight "the role of AI in replicating and replacing the human workforce" (Tursunbayeva et al., 2021, p. 15) owing to the ability of AI "to perform tasks that normally require human cognition, including adaptive decision making“ (Tambe et al., 2019, p. 16). Overall, several scholars stress that advances in the field of AI will transform employees' work processes, and even have the potential to substitute work processes previously inherent to human decision-making (Faraj et al., 2018; von Krogh, 2018).

Although some of the more recent literature on people analytics references the increasing technological advancement's role in the context of people analytics, current literature lacks a systematic reflection of the effects these new technologies might have for organisations and their employees. To account for the introduction of learning algorithms in the context of workforce management and the potential aggravation of the risks of people analytics (Leicht-Deobald et al., 2019; Simbeck, 2019), we propose a fourth maturity level: autonomous analytics. This maturity level relies heavily on the use of autonomous learning algorithms, mostly based on artificial neural networks to process structured, unstructured, and self-updating data from various sources (Margherita, 2021; Tambe et al., 2019). Thereby, autonomous analytics differs from other systems in learning capacity, i.e., with every application autonomous analytics can improve and provide more precise estimations and evaluations and autonomously adapt decision parameters (Davenport, 2018; Krumeich et al., 2016; Wang, 2012). These types of algorithms and models are no longer deterministic, predictable or strictly repeatable processes and calculations (Dourish, 2016). Whereas descriptive, predictive and prescriptive analytics serve as supplementing technologies and decision-support systems, analytics in this new maturity level autonomously drives decision-making to substitute human intervention (Kellog et al., 2020; Pachidi & Huysman, 2018; von Krogh, 2018). Consequently, autonomous analytics does not focus on a specific type of human-driven question to assist decision-making, as it was the case with the maturity levels outlined above. Instead, the decision-making authority is transferred from humans to AI-enabled people analytics' systems. Thus, unlike previous levels of analytics, technologies on the fourth maturity level can also autonomously substitute decision-making processes, including the execution of task and entire work processes (Mayer et al., 2020; Strich et al., 2021). Overall, by dictating an entire decision process, as well as automatically executing and even communicating the derived decisions, technologies used by autonomous analytics can substitute humans in the decision-making process (Burton et al., 2019; Strich et al., 2021).

Recent advances highlighted in the fourth maturity level have further reinforced the high expectations organisations hold regarding the implementation and use of people analytics technologies to manage their workforce. Expectations based on the assumptions that learning algorithms are superior to human decision-making (Kryscynski et al., 2018; Leicht-Deobald et al., 2019), can adequately predict future human behaviour based on historical data (Chamorro-Premuzic et al., 2017; Gal et al., 2017; Isson & Harriott, 2016), and are equally applicable in managing inanimate objects and animate objects (such as humans) (Gal et al., 2017, 2020; Leicht-Deobald et al., 2019). Such expectations are informed by practices already used in related fields such as business analytics (Holt et al., 2017; Isson & Harriott, 2016) and are associated with increased productivity, higher performance, effective management and lower personnel costs.

Yet, the peculiarities we depicted in our literature review illustrate the danger of applying the logic developed in other business analytics areas to people analytics. If the unique aspects of people analytics are not diligently considered, utilising technological practices similar to those in other fields can bring risks that have unintended consequences at an organisational as well as an individual level. Such risks might aggravate due to recent technological advancement and the nascent introduction of learning algorithms in the field of people analytics. We believe that most of these emerging methods and technologies have yet to be rigorously scrutinised in scientific research to take the field beyond the dominant paradigm that one-sidedly highlights the benefits of how organisations and employees could prosper from the use of people analytics. Consequently, we need to identify and challenge the underlying assumptions of the current literature (Alvesson & Sandberg, 2011) and illustrate how these assumptions can aggravate in severe perils of people analytics.

3. The perils of people analytics for organisations and employees

The methodological approach for identifying our perils is informed by Leidner (2018) and is grounded in a broad theorising review of the organisational expectations associated with using learning algorithms in people analytics. We conceptualise perils as risks resulting from the use of people analytics and the unintended and harmful implications they have for organisations and employees. In introducing each peril, we reconstructed the promises organisations rely on, as well as the assumptions and expectations they have with a view to decision-making, management and human capabilities related to the use of people analytics (Alvesson & Sandberg, 2011). Then, we unpack the potential risks and consequences, and theorise about the tensions around people analytics' undesired and potentially harmful implications for organisations and employees. In line with previous research (Gal et al., 2020; Pachidi & Huysman, 2018), we maintain that our perils are not necessarily intentionally induced. Further, we acknowledge the recent rapid technological advancements and highlight how future development may aggravate the risk resulting from the identified perils and potentially change current HR and management practices. We illustrate these implications with organisational examples based on current practices in the people analytics field. Overall, our phenomenon-driven approach (Leidner, 2018) provides a comprehensive theorising review to highlight the potential effects of AI in managing the workforce, raising awareness of the potential perils, and advancing the field of people analytics to meet future challenges. In the following section, we elaborate on the six identified perils of people analytics and theorise about the consequences for organisations and employees.

3.1. People analytics can bring about an illusion of control and reductionism

People analytics builds on the belief that digital data can accurately represent reality and objectively quantify the full scope of workforce activities and employees' traits, experiences and skills (Faraj et al., 2018; Gal et al., 2017). With its ability to analyse vast amounts of data related to employees' traits, experiences and skills, people analytics promises to deliver an accurate and objective account of employees' performance (Tursunbayeva et al., 2018).

However, people analytics can promote a false sense of certainty regarding the data (Gal et al., 2017), which can lead to two major pitfalls. First, people analytics' illusion of objectivity can result in an overly strong, possibly even a blind belief in the algorithms' processes, results and capability to predict reliable outcomes correctly (Leicht-Deobald et al., 2019; Mayer et al., 2020). Such unwarranted trust and overconfidence in the ostensible objectivity and rationality of machines could create an illusion of control in that managers and employees might overestimate their ability to influence decisions over which they actually have little control (Kellog et al., 2020; Newell & Marabelli, 2015). As people analytics' analytical power increases, this perception of control can increase, which raises the likelihood of underestimating risks (Durand, 2003).

Second, people analytics might follow a reductionist logic which can mislead managers to postulating cause-and-effect relationships that in fact do not exist (Bhattacharya et al., 2010; Khan & Tang, 2017; Leicht-Deobald et al., 2019). Algorithms represent a simplified model of human behaviour that is restricted to a set of measurable dimensions or proxies of such behaviour (Faraj et al., 2018; Gal et al., 2017; Hansen & Flyverbom, 2015). Such an oversimplification of complex features can misrepresent reality (Dulebohn & Johnson, 2013; Pachidi & Huysman, 2018). By putting people into boxes, people analytics systems fail to consider the complex, decisive nature of knowledge work and human interaction (Faraj et al., 2018; Gal et al., 2017).

For example, Microsoft's tool, MyAnalytics, promises to make organisations' knowledge workers more productive by analysing and optimising their individual workflows (Clohessy et al., 2018). In doing this, the tool evaluates employees' email traffic, response time, and time spent in meetings. While Microsoft may have intended to give employees an overview of their work routines to optimise their time resources, the tool also enables HR to gain a detailed measure of employees' behaviour (Fuller & Shikaloff, 2017; Hodgson, 2019). This, in turn, allows the firm to identify the most productive workers and to include such information in the company's decision-making. Nonetheless, the practices such tools capture are most likely incomplete, reductive and a potentially misleading representation of the knowledge workers' actual work (Gal et al., 2020; Pachidi & Huysman, 2018). Consequently, this measurement can lead to costly decisions, such as promoting and dismissing the wrong people, and establishing perceptions of unfairness among employees (Khan & Tang, 2017). As this example shows, people analytics risks reducing valuable qualitative, even if tacit, aspects of employees' performance to quantifiable metrics, thus failing to adequately consider all aspects of performance and contextualise human qualities more broadly (Newman et al., 2020). Such quantification and decontextualisation could be damaging to companies, as if they promote and lay off the wrong people, with detrimental consequences for both organisations and employees (Khan & Tang, 2017; Newman et al., 2020).

Hence, it is important that HR managers and employees are aware of such reductionist tendencies. Once reductionism is masked in the data, people tend to perceive constructs, such as performance, as objective realities (Cowgill & Tucker, 2020; Gal et al., 2017). Reductionism is therefore particularly harmful when it is no longer recognised and insufficiently reflected upon in the managerial decision-making process (Curchod et al., 2020; King, 2016). This can become particularly problematic if more advanced forms of people analytics, such as prescriptive or autonomous analytics, are deployed. For instance, learning algorithms aim to autonomously optimise and adapt decision-making processes, even if the underlying data may already be subject to reductionistic tendencies. Consequently, the identification of potential reductionistic tendencies will most likely become more complicated the more advanced the technologies in use are.

Put simply, people analytics might not always live up to the inflated expectations and promises of objective knowledge (Bodie et al., 2016; Leicht-Deobald et al., 2019). The illusory objectivity of people analytics algorithms can also obfuscate the assumptions and underlying reductionism built into these technologies, resulting in less accurate information (Bhattacharya et al., 2010; Gal et al., 2020; Leicht-Deobald et al., 2019; Newman et al., 2020; Pachidi & Huysman, 2018). Consequently, organisations risk creating dysfunctionalities, flawed strategic decision-making, taking misdirected actions, and undermining their employees' development (Durand, 2003).

3.2. People analytics can lead to estimated predictions and self-fulfiling prophecies

People analytics rests on the assumption that it can explain, predict and modify human behaviour based on past events (Cappelli, 2019; Pachidi & Huysman, 2018). With a growing shortage of skilled labour, organisations are hoping that people analytics will anticipate future workforce trends, derive proactive courses of action, and optimise the recruiting of employees as a scarce strategic resource (Bodie et al., 2016; Chamorro-Premuzic et al., 2017; Huselid, 2018; Minbaeva, 2018; Peeters et al., 2020).

However, the predictions people analytics and its deployed algorithms make are merely conditional probabilities for the occurrence of an event, not the event itself (Faraj et al., 2018). This means that people analytics assesses on the probability of employees showing certain behaviours rather than on their actual behaviour (Brayne, 2017; Faraj et al., 2018; Mayer-Schönberger & Cukier, 2012). The upshot is that people are subject to how the algorithm categorises them (Faraj et al., 2018; Fourcade & Healy, 2013). Examples such as the epic failure of Google Flue Trends (Lazer & Kennedy, 2015) or from the field of crime analytics, where inmates were granted parole, based on the likelihood of not committing a crime illustrate that these probabilistic predictions can result in erroneous assignments of a high risk (Brayne, 2017; Faraj et al., 2018; Huysman, 2020; Israni, 2017). This can have worrying implications in the people analytics context. For instance, people analytics could develop a pattern to detect the likelihood of future absence from work (e.g., pregnancy) or illness (e.g., mental health issues, such as burnout, depression); these probabilities could be integrated in decisions to hire or lay-off (compare Boot et al., 2017; Boudreau, 2014; Duhigg, 2012; Thorstad & Wolff, 2019). Managers are often unaware of the conditional nature of estimated predictions and their respective statistical limitations (Boudreau & Cascio, 2017; Khan & Tang, 2017). This risks that managers view the estimates as accurate predictions and execute the proposed decisions without due caution (Hamilton & Sodeman, 2020). Furthermore, this can lead to serious misjudgements and detrimental outcomes for both organisation and employees when more advanced forms such as autonomous people analytics are deployed and there is no longer a human counterweight to algorithmic categorisation and decision errors (Shrestha et al., 2019). The inherent complexity of learning algorithms further aggrevates the recognition of potentially faulty controls. The more accurate technologies apparently become in predicting simple relationships, the greater the confidence of decision makers to rely on these technologies in highly sensitive areas of decision making.

Further, applying people analytics can lead to self-fulfiling prophecies (Batistic & van der Laken, 2019; Herschel & Miori, 2017; Peeters et al., 2020). Following people analytics' predictions, organisations and managers can take decisions which create conditions that ultimately realise these very predictions (Gal et al., 2017; Rainie & Anderson, 2017). For instance, firms can use people analytics to forecast the future performance, the expected retention, or return on investment in their recently hired employees (Boudreau & Cascio, 2017; Chalutz, 2019; Kellog et al., 2020; Pessach et al., 2020). Then, based on these predictions, companies might allocate training resources only to the employees they perceive as promising, which will result in selected employees receiving additional training, while others receive no training (Cowgill & Tucker, 2020; Gal et al., 2017). Such actions will produce exactly the predicted results: employees who receive training will outperform those who do not receive training (Gal et al., 2017; Simbeck, 2019). However, the difference between the two groups of employees can mistakenly be interpreted as indicators of the validity of people analytics (Calvard & Jeske, 2018; Gal et al., 2017; Simbeck, 2019), while the performance improvement might be due to the additional training and not related to people analytics' predictive power.

In sum, the assumption that people analytics can reliably and validly predict human behaviour based on past events can mislead managers to draw problematic conclusions and implement weak decisions (Boudreau & Cascio, 2017; King, 2016). Such decisions can lead to serious misallocation of organisational resources (Boyd & Crawford, 2012; Huselid, 2018).

3.3. People analytics can foster path dependencies

A central assumption of people analytics is that it enables decision-makers to predict future human behaviour based on historical data (Chamorro-Premuzic et al., 2017; N. Wang & Katsamakas, 2019). This way, people analytics is meant to help organisations solve critical problems, identify and predict future trends, facilitate strategic workforce planning, and adapt to business and market trends (Hansen & Flyverbom, 2015; Schildt, 2017; Sharma et al., 2014; Tursunbayeva et al., 2018).

However, by drawing on historical data to predict and prescribe the future, algorithms "embody a profound deference to precedent" (Barocas et al., 2013, p. 8). Consequently, based on people analytics, firms predict future events only as an extrapolation of the past, thus only focusing on actions that proved to be successful in the past while ignoring novel patterns and parameters (Pachidi & Huysman, 2018). Yet, such an approach makes companies more vulnerable to external shocks. For example, in the Covid-19 situation employees will partly change their behaviour in ways that an algorithm had not foreseen in using data from before this crisis. A prediction of employees' preferences for home offices would have been completely wrong if the data had been collected before the pandemic broke out. As such, predicting future behaviour based on historic data implies an extrapolation of the future based on past patterns. The literature on strategic forecasting is a telling example of how difficult it is to foresee future trends and developments, and how those predictions often prove to be wrong due to changes in the wider ecosystem (e.g., Appelbaum et al., 2017; Durand, 2003; Lazer & Kennedy, 2015).

Consequently, firms can encounter the risk of path dependency, which limits their capacity to innovate (Sydow et al., 2009). Thus, people analytics can result in self-perpetuating loops solidifying the direction of development regardless of its quality (Barocas et al., 2013). For instance, Amazon set out to automate its talent search by relying on a prescriptive analytics tool to identify the top candidates based on profiles of successful hires over the past 10 years. As the data showed that the overwhelming majority of successful hires had previously been (white) men, the tool predicted that male candidates were more likely to be a good fit; thereby, the algorithm inappropriately excluded women (Hamilton & Sodeman, 2020; Purdy et al., 2019; Simbeck, 2019; Vardarlier & Zafer, 2020). As a result, Amazon had to abandon the recruitment tool (Dastin, 2018; Hamilton & Sodeman, 2020; Peeters et al., 2020).

As this example underscores, hiring decisions based on historical data can result in homosocial reproduction, homophily, social bias, and discriminatory practices (Hamilton & Sodeman, 2020; Kellog et al., 2020). It also demonstrates how advances in people analytics technology can exacerbate these risks, because the more algorithms automatically make decisions, the more information based on complex models is provided, the higher the risk of covert discrimination. Consequently, the use of and reliance on learning algorithms and AI can reinforce social and economic stratification, inequality and the social isolation of minorities (Barocas et al., 2013; Bodie et al., 2016; Kellog et al., 2020; Kleinbaum et al., 2013; Simbeck, 2019). Importantly, the increasing uniformity can, in turn, lead to innovations being nipped in the bud, as well as to diverse and creative approaches in organisations being curtailed (Gal et al., 2017).

Accordingly, people analytics can also impede the decision-making horizon and significantly limit access to alternative perspectives, novel ideas and knowledge diversity (Faraj et al., 2018; Kleinbaum et al., 2013).

Overall, the use of people analytics potentially bears the risk that organisations will act backward looking, deterministically, ego-centrically and bounded by their very own algorithms, which can lead to the firms repeating past mistakes (Cappelli, 2019; Pachidi & Huysman, 2018; Simbeck, 2019). By focusing on past events to determine their future strategy, organisations can become less open, less innovative and less flexible in responding to changes in their internal and external environment (Thrane et al., 2010).

3.4. People analytics can impair transparency and accountability

By creating more transparent HR processes, people analytics is meant to answer the increasing organisational demand for managers to be more accountable regarding their activities and the logic of their decisions (Flyverbom, 2019; Giermindl et al., 2017; Leonardi & Contractor, 2018; Stohl et al., 2016). In this respect, people analytics promises that employees will benefit from fairer, more understandable HR decisions, which in turn will increase their participation opportunities, as well as their commitment and work motivation (Isson & Harriott, 2016; Minbaeva, 2018; Newman et al., 2020; van den Broek et al., 2019).

With increasing analytical power, however, the decisions made by people analytics become more and more opaque, inaccessible and untraceable regarding their underlying assumptions, mechanisms and processes (Faraj et al., 2018; Pachidi et al., 2016; Simbeck, 2019). When less advanced forms of people analytics, such as descriptive or predictive analytics, are used for decision-making, employees can gain insight in the logic that guided their decisions by asking their managers to disclose the reasons for their decisions (Gal et al., 2020; Leicht-Deobald et al., 2019). Once advanced machine learning algorithms are deployed, only a limited group of knowledge workers with highly specialised skills and technical training can reconstruct decisions (Dourish, 2016; Faraj et al., 2018). Thus, Burrell (2016) emphasises:

> "When a computer learns and consequently builds its own representation of a classification decision, it does so without regard for human comprehension [...] The workings of machine learning algorithms can escape full understanding and interpretation by humans, even for those with specialized training, even for computer scientists" (Burrell, 2016: 10).

Ultimately, learning algorithms can become too complex to be fully understood even by those programming them (Dourish, 2016; Gal et al., 2017; Possati, 2020). For example, in the context of people analytics, this implies that pivotal decisions such as on staff layoffs, could be made even without the responsible manager exactly knowing why and how the algorithm decided to do so. As the manager will no longer be able to explain the decision rationales, employees could perceive the decisions as arbitrary or nonsensical, resulting in complaints of unfairness, feelings of frustration or disengagement, and possibly high employee turnover (Flyverbom, 2019; Gal et al., 2020; Huysman, 2020; Zarsky, 2016).

Another example, in the context of drug testing, which is increasingly used by organisations in the recruiting process (Calmes, 2016), shows how false positive decisions can have different causes, such as medication or test procedures in laboratories (Akin, 2020; Bodie et al., 2016). Yet, such false positive results can deprive workers of their jobs or tarnish their reputations for future opportunities (Bodie et al., 2016; Kellog et al., 2020). This is particularly problematic, not only because of potential bias and high stakes, but also because workers might not be able to appeal judgements against them or correct missing or mistaken information (Kellog et al., 2020). Owing to the data's high opacity and the limited access to it, it can be difficult to reverse engineer the data to ensure its accuracy (Bodie et al., 2016).

Further, the opacity of algorithms raises the question of who is accountable for a managerial decision and its ethical implications (Ananny & Crawford, 2018; Hansen & Flyverbom, 2015). Accountability refers to the expectation that a person can be called on to justify his or her intentions, motives and rationalities (Gal et al., 2017). By allocating decision-making authority to autonomous people analytics, organisations could be tempted to avoid accountability (Barocas et al., 2013; Martin, 2018; von Krogh, 2018). However, given the potentially life-altering nature of algorithmic decisions in the people analytics context, as depicted in the examples above, organisations should be wary of the risks and negative consequences posed by relying on these systems, and they should work to hold their people analytics algorithms accountable (Calvard & Jeske, 2018; Diakopoulos & Friedler, 2016).

Yet, to hold algorithmic decision-making systems accountable for their outcomes requires more than seeing the algorithm's code or the underlying data; rather, one needs to clearly understand how the system works and should be able to reconstruct the reasons for the algorithmically computed decisions ex-post facto (Ananny & Crawford, 2018; Barocas et al., 2013; Bodie et al., 2016). Nonetheless, although the deployed algorithms are inscrutable or impossible to understand, organisations need to take responsibility for their outcomes and ethical implications (Martin, 2018).

Overall, if the deployed learning algorithms and AI function as a black box, it seems difficult to determine who can be held accountable for serious mistakes, significant failures, and misconduct of a system (Ananny & Crawford, 2018; Diakopoulos & Friedler, 2016; Huysman, 2020). Such opacity can create information asymmetries, obscure power structures and inhibit oversight, as well as negatively influence workers' perceived procedural fairness and organisational commitment (Gal et al., 2020; Jabagi et al., 2020; Newman et al., 2020). Further, prior research suggests that when workers are directed by an algorithm that they perceive as unfair, this can undermine their moral compass and increase their willingness to engage in unethical behaviour (Curchod et al., 2020; Kellog et al., 2020). Consequently, employees could lack legal certainty and feel powerless, while managers might feel incapacitated by such algorithms (Curchod et al., 2020; Kellog et al., 2020; Leicht-Deobald et al., 2019).

3.5. People analytics can reduce employees' autonomy

People analytics can support the organisational need for knowledge intensive, flexible or even new, fluid organisational forms by improving collaboration between employees and by leveraging their innovative and creative skills (Holford, 2019; Minbaeva, 2018; Tursunbayeva et al., 2018). Further, it promises to increase employees' scope for decision-making, autonomy, and self-management competences (Bodie et al., 2016; Minbaeva, 2018).

Even so, people analytics can also significantly curtail employees' autonomy and their reflexive self-determination (Jabagi et al., 2020; Leicht-Deobald et al., 2019; Schafheitle et al., 2019). Thus, people analytics can impede employees' genuine discretion in decision-making and working habits by replacing teams' interactive processes, collaboration and cooperation practices with pre-defined goals and key performance indicators (KPIs) condensed in algorithms (Burton et al., 2019). In this way, people analytics can produce reactive chains of action instead of self-reliant and self-organised behaviour according to employees' self-determination. As a result, algorithmic calculation can become more relevant than people's self-determination, corroding the open social processes of teams (Burton et al., 2019; Mayer-Schönberger & Cukier, 2012). A phenomenon, that potentially continues to intensify, with the use of increasingly advanced technologies such as learning algorithms or AI.

For instance, O'Connor (2016) reports on a Silicon Valley-based people analytics software provider named Percolata that seeks to maximise employees' retail performance and workers' productivity for a variety of retail chains. To achieve this, the software combines sensor-based human movement patterns with data on the amount of sales per employee (i.e., sales divided by customers). Percolata provides management with detailed reports on when and with which colleagues each employee performs best, including a list of employees rated from lowest to highest by shopper yield. Based on these prescribed actions, the company supplies a schedule with the ideal mix of workers to maximise sales for every 15-minute slot of each day, giving the worker with the highest shopper yields more hours than their lower performing colleagues. The only role left for managers is to press a button so that the schedule is automatically communicated and instantaneously sent to workers' personal smartphones, thus replacing communication between employees and managers (O'Connor, 2016). This example shows that people analytics software can replace direct communication with a human manager, removing managers interacting to give feedback and in-person assessment of workers (Gray & Suri, 2019; Kellog et al., 2020).

In the context of knowledge workers, people analytics or tools such as Microsoft's MyAnalytics can be used similarly to the way in which the Percolata example did to identify, pressurise and eliminate low performers (Fuller & Shikaloff, 2017; Hodgson, 2019). As has already become evident in gig economy firms such as Uber, UberEats and Deliveroo, this could even go further, with algorithms automatically notifying underperforming workers of their dismissal (via a dashboard) without any human involvement (O'Connor, 2016; Schildt, 2017). People analytics risks fostering similar conditions in the context of knowledge workers (Gray & Suri, 2019). Prior research has labelled this renewal of the Taylorist paradigm as digital Taylorism and "involves creative and intellectual tasks being subject to the same process as chain work" (Holford, 2019, p. 5). This way, the algorithms deployed by people analytics can now control humans in an unprecedented and alarming way (Faraj et al., 2018; Kellog et al., 2020; Schildt, 2017). Thus, algorithms "[provide] a degree of control and oversight that even the most hardened Taylorists could never have dreamt of" (Prassl, 2016; as cited in O'Connor, 2016).

Overall, the reductionist mapping of complex human abilities and characteristics according to a machine paradigm heralds in a new era of algorithmic management and control. The examples

Table 4. Evolution of the perils of people analytics at the respective maturity levels.

Maturity Level	Descriptive People Analytics	Predictive People Analytics	Prescriptive People Analytics	Autonomous People Analytics
Decision Process	**Decision Support**		**Joint Human-Algorithm Decision-Making**	**Automated Decision-Making**
Characteristics	People analytics analyses what happened in the past and how this influences the present.	People analytics forecasts future developments based on past or real-time observations and probabilistic weighting of various scenarios.	People analytics automatically prescribes decision recommendations based on advanced statistics, scenarios and machine learning algorithms.	People analytics autonomously derives complex decisions, executes them, and communicates them based on self-learning algorithms.
Human/Machine Interaction	People analytics gains acceptance as it provides support by facilitating managers' drawing conclusions from evaluated past data to make data-driven decisions.	Organisations and employees increasingly rely on people analytics for decision-making and question these systems less and less.	Owing to its seeming superiority, employees tend to trust the decisions blindly and to implement the proposed recommended measures unquestioningly.	Much of the decision-making and execution process is automated and is increasingly performed without human interaction, expertise, or reflection.
1. People analytics can bring about an illusion of control and reductionism	• Employees can be guided by the false expectation that digital data can accurately and objectively represent reality which can lead to a false sense of certainty. • This bears the risk that they overlook the emerging reductionism and postulate non-existing cause-and-effect relationships.	• There is a risk, that managers and employees justify their decisions based on reductionist parameters and increasingly rely on the illusion that they can control the future. • This overconfidence can lead to insensitivity to feedback and inaccurate risk assessment.	• Employees may blindly trust the supposedly unchangeable technological decision; although they may believe they are still in control, they have delegated their decision-making authority. • The implementation of the decision made by people analytics without critical scrutiny can lead to costly poor decisions and misguided strategies.	• The illusion of control and blind faith in the algorithms may increasingly cause employees to consign the decisions completely to people analytics technology; thus, it becomes even more difficult to recognise reductionism or errors in the data. • The result is mismanagement, of which the causes may no longer be identified, undermining the workforce's potential.
2. People analytics can lead to estimated predictions and self-fulfiling prophecies	• This peril only occurs if predictive analytics or more advanced forms are applied.	• Organisations are less likely to recognise that predictions are based only on forecast probabilities and may fail to recognise the resulting self-fulfiling prophecies. • This misleads organisations into believing that they can predict future behaviour, which can lead to wrong conclusions and decisions.	• Managers and employees tend to regard the estimates as accurate predictions and implement the proposed decisions without reflection. • Self-fulfiling prophecies may confirm the previously made assumptions, which encourages employees to keep trusting and following the prescribed decision recommendations.	• The executed decisions can misjudge the estimated predictions and self-fulfiling prophecies. • Self-fulfiling prophecies may become increasingly prevalent, as they strengthen and continue in a self-affirming cycle, often resulting in the misdirection and misallocation of organisational resources.
3. People analytics can foster path dependencies	• Due to its historical orientation, people analytics has limited transformational potential. • However, self-determined human interventions can still compensate for such a limitation.	• Organisations predict future events only as an extrapolation of the past, which makes organisations more vulnerable to external shocks. • There is a risk that organisations fail to recognise the arising path dependencies which can systematically undermine future orientation and innovation.	• Organisations and employees tend to overlook the actual developments and the need for adaptation. • The unrecognised path dependencies can result in self-perpetuating loops solidifying the direction of development regardless of its quality, impeding the decision-making horizon and limiting access to alternative perspectives and novel ideas.	• There is a danger that organisations systematically exclude human decision-making power and become purely self-referential without organisational foresight. • Organisations may become less open, less innovative, and less flexible in responding to changes in their internal and external environment.
4. People analytics can impair transparency and accountability	• Only employees with advanced statistical knowledge can retrace the decision rationales. • Accountability for the analytics-supported people-related decisions still lies with the managers and employees can still approach them to have their decision rationales disclosed.	• The algorithms and justifications underlying the decisions are largely opaque and more and more difficult to understand. • Accountability for the data-driven and technologically derived decisions still lie with the managers, but they may no longer be able to explain and justify these in a rationally comprehensible way.	• The algorithms may be too complex to be understood by employees affected by their application as well as managers who apply them. • Accountability can no longer be meaningfully assigned to a human at the specific level of decision-making and action, and decisions may be increasingly perceived as arbitrary and nonsensical.	• The decisions and actions can be incomprehensible and irretraceable for employees, the organisation, and even the analytics technology provider. • It is hard to hold anyone accountable for the decisions. This can result in feelings of powerlessness of employees and incapacitation of managers, as well as in potentially creating information asymmetries, obscuring power structures, and inhibiting oversight.

(Continued)

Table 4. (Continued).

Maturity Level	Descriptive People Analytics	Predictive People Analytics	Prescriptive People Analytics	Autonomous People Analytics
5. People analytics can reduce employees' autonomy	• People analytics can impede employee discretion in decision making by replacing teams' interactive processes and collaboration practices with predefined goals and algorithmically condensed KPIs. • Mechanised management procedures can inhibit employees' own performance and self-control potential.	• Predictive future events based on standardised patterns bear the risk to lead to a mechanisation of human thinking and behaviour. • The sphere of decisions and actions as well as employee autonomy may become increasingly restricted and can produce reactive chains of action instead of self-reliant and self-organised behaviour according to employees' self-determination.	• There is a risk that both individual and cooperative decision-making processes will become increasingly mechanised and semi-automated and less reflected by open, individual, or cooperative cognitive processes. • People analytics is increasingly replacing direct communication with a human manager and controlling employees, which reduces their autonomy, freedom, and self-organisation skills.	• Organisations relying too heavily on people analytics run the risk of developing into a mechanistic neo-tayloristic system in which the complexity of the human and social sphere is hardly recognised. • This can lead to alienating and dehumanising work and to reification of interpersonal relationships, whereby workers will experience a loss of individuality, autonomy, and reflexive self-determination.
6. People analytics can marginalise human reasoning and erode managerial competence	• Due to the alleged superiority of people analytics, managers may be tempted to trust and feel social pressured to rely on people analytics. • Managers may tend to put aside their intuitions and abilities and if in doubt, act against their own assessments.	• Human rationality is still involved in accepting/rejecting the automated insights: managers can still discern when and where not to incorporate the algorithm's judgment in their own decision-making. • Yet the value, relevance and need for genuine human decision-making competences can start to decrease and managers progressively forfeit their sense-making capabilities.	• There is a risk that sovereignty over decisions is increasingly passing over from managers to people analytics. • This can drastically undermine managers' power of judgment, human reasoning, and critical reflection and can lead to devaluing of the management function.	• Managers have less and less opportunities to take decisions, and people analytics may operate without human judgement to mitigate their operation. • Managers increasingly lose their ability to make rational decisions human reasoning, rationalising, and sense-making atrophy and managers increasingly become obsolete.

given above demonstrate that people analytics can revive the piecemeal system with an algorithmic managerial span of control of which the logic is opaque (Faraj et al., 2018). While coordinating work can become more efficient in using people analytics, it can ultimately lead to mechanising the workplace and to working environments in which individual employees have little or no direct human contact with one another, thus undermining the organisation's appropriate development and its innovative power (Dahlander & Frederiksen, 2012; Dougherty & Dunne, 2012; Faraj et al., 2018). Furthermore, recent technological advances such as autonomous analytics can further aggravate the alienation and dehumanisation of work. Whereas the supervision and monitoring of work processes was previously limited by personnel and thus also financial resources, this can now be carried out in real time by learning algorithms without the need for human interaction. Therefore, organisations relying on people analytics can lead to the reification of interpersonal relationships, whereby workers will experience a loss of individuality, autonomy and individual freedom (Curchod et al., 2020; Holford, 2019; Kellog et al., 2020).

3.6. *People analytics can marginalise human reasoning and erode managerial competence*

One core argument of people analytics is that managerial decision-making should be a more rational process in which algorithms guide decision-making, because humans are subject to inherent unconscious biases, unrecognised overconfidence and irrational behaviour (Burton et al., 2019; Gal et al., 2017). Owing to its large processing power, people analytics promises to help managers make more effective HR decisions, to complement their competences, and to promote rationality in managerial decision-making and human sense-making (Lee, 2018; Leicht-Deobald et al., 2019; Werkhoven, 2017b).

However, people analytics can simultaneously decrease the value, relevance and need for genuine human decision-making competences (Gal et al., 2017; Mayer et al., 2020). If organisations consider algorithms to be superior and more objective than allegedly emotional, subjective and deficient human processes, and they find managers' only valid source of knowledge should be measurable, and preferably quantitative facts, human abilities and managerial competence will necessarily be devalued (Gal et al., 2017; Leicht-Deobald et al., 2019; Newell & Marabelli, 2015). The seeming superiority of people analytics can lead employees to trust these technologies and systems more than either their own assessment of current circumstances or their unique capabilities such as their intuitive judgement, reasoning and critical reflection (Burton et al., 2019; Introna, 2016; Leicht-Deobald et al., 2019; Mayer et al., 2020). Further, employees might feel social pressured to rely on these people analytics tools and to follow their recommendations to avoid the risk of being held responsible for poor decisions (Briône, 2017; Leicht-Deobald et al., 2019; Pachidi & Huysman, 2018; van den Broek et al., 2019). Consequently, human qualities such as problem solving and creativity could increasingly give way to calculation, efficient predictability and control (Ananny, 2016; Orlikowski & Scott, 2014).

For example, at the Siemens factory in Congleton, a software called Preactor was introduced to give the workshop teams instructions on which parts to produce and in what order. Rather than relying on their human judgment and experience, workers now receive a specific set of instructions from the software telling them exactly in what order to perform each step. While the cell managers welcomed the clarity and simplicity of the production and action plans, production workers complained about their loss of autonomy and the devaluation of their skills and knowledge. The algorithmic decision templates stepped in, compromising the former social relationships between management and production employees and making it impossible for managers to adequately assess the new system's negative effects on employees (Briône, 2017).

As this example already indicates, this development could end in a vicious circle in which the more employees' decision-making is substituted by people analytics, the less opportunities and autonomy they have to make their own decisions, whereby their learning capacities are also reduced (Pachidi & Huysman, 2018). The technological advances in people analytics might further exacerbate this phenomenon: the more autonomous respective algorithms are, the less need there is for humans to monitor, review or improve them. Accordingly, the need for human expertise decreases as technologies' autonomy advance. As with muscles that are not trained, employees' power of judgment and reasoning atrophies over time and their ability to make independent decisions can gradually wither away.

Managers, leaders and decision-makers are particularly affected by marginalisation of human sense-making, reasoning, and rationalising (Curchod et al., 2020; Gal et al., 2017; Jabagi et al., 2020). To date, successful team leaders have often excelled in making good strategic decisions regarding team composition. They selected, developed and promoted employees based on their closeness and interaction with their team, relying on non-conscious forms of cognition as well as explicit reasoning processes (e.g., Hackman & Wageman, 2004; Hodgkinson et al., 2009). Every time managers delegate information gathering and decision-making to algorithms and limit their own thinking to what the algorithms deem appropriate, they risk forfeiting their cognitive autonomy (Burton et al., 2019). Thus, algorithmic evaluations and decisions can replace, reshape and interrupt the relationship between manager and employee, which de facto can lead to devaluing the management function (Curchod et al., 2020; Gal et al., 2017; Jabagi et al., 2020; Jarrahi et al., 2019). When managers start to merely rely on the choices prescribed by people analytics rather than on their experience, they risk making themselves redundant.

One example is a high-skilled online labour market system that replaced a transparent evaluation of employees with a non-transparent automated evaluation and wage calculation. Employees no longer understood the evaluation criteria and how they determined their rating and the resulting pay cuts. Negotiation processes between management and employees became redundant, as did discussion between employees and management about the meaningfulness of tasks and evaluations. An algorithm instead of a person on the other side of the managerial relationship reduces contact between managers and workers, so that employees can no longer question or challenge their directions and results (Kellog et al., 2020).

Overall, the seeming infallibility of people analytics and an organisations reliance on it can disrupt and lower employees' powers of judgment (Holford, 2019). Further, the increasing transfer of traditional management tasks to people analytics systems can marginalise decision-makers' mental representations, sense-making and rationality (Gal et al., 2017; Pachidi & Huysman, 2018). Ultimately, the use of and reliance on learning algorithms and AI as used in autonomous analytics is likely to aggravate the erosion of managerial competences and could even reduce their role to that of the machine's stooge (Faraj et al., 2018; Schildt, 2017), and lead to the organisation replacing managers, to the extent that many could become obsolete (Faraj et al., 2018; Gal et al., 2017; Schildt, 2017). For employees, this would mean that they have no one to turn to in trying to understand problems they need to solve, or in making a decision or seeking feedback on their work. This can lead to employees experiencing frustration, anxiety and stress (Gray et al., 2016; Schwartz, 2018).

3.7. Summary and integration

The six perils discussed above reveal the potential dangers, tensions and risks of the use of people analytics. While some may still sound like a farfetched dystopian scenario, the perils exist today, albeit in a less pronounced and evident form. As mentioned, we argue that technological advancements and the nascent introduction of learning algorithms and AI in the field of people analytics have the potential to enlarge and aggravate the risks of people analytics and their potential profound negative impacts on organisations and employees. To illustrate the characteristics and evolution of these perils, we have juxtaposed each of them with the four levels of maturity to form a matrix in Table 4. It serves as an overview of the characteristics and stages of development of the six identified perils and shows how they evolve and aggravate with each maturity level. While the opportunities for organisations increase with each stage of development due to the progress of the underlying technologies, at the same time the impact of the perils on organisations and employees may be escalating.

4. Discussion

In this paper we set out to identify potential perils of people analytics and to theorise about their potential negative consequences for organisations and employees. We first systematically reviewed the people analytics literature and openly mapped the research field using a theme-centred reviewing approach (Leidner, 2018; Rowe, 2014; Webster & Watson, 2002), categorising this literature's emerging themes, patterns and trends. We identified five emerging themes relating to the opportunities, barriers, maturity, idiosyncrasies and risks of people analytics. Further, we uncovered some underdeveloped areas in this nascent field of research, such as the lack of rigorous quantitative and qualitive empirical studies on people analytics' outcomes, or the limited analysis of more advanced forms of people analytics' uses, and we suggested future research avenues for each theme. To account for the recent technological advancements and the nascent introduction of learning algorithms and AI in the field of (people) analytics, we proposed a new maturity level, autonomous people analytics.

Thereafter, we unpacked and challenged several underlying assumptions held in a good portion of the academic and practitioner-oriented discourse on people analytics. These assumptions evolve around the notion that recent technological advances in people analytics tend to be more objective than and superior to human decision-making (e.g., Bodie et al., 2016; Kryscynski et al., 2018; Martin-Rios et al., 2017), that people analytics can reduce bias and increase transparency (Jabagi et al., 2020; Martin-Rios et al., 2017; Sharma & Sharma, 2017), that future behaviour can be precisely extrapolated based on current or past behaviour (e.g., Chamorro-Premuzic et al., 2017; Gal et al., 2017; Sivathanu & Pillai, 2019), and that learning algorithms can be equally applied in handling inanimate objects and managing humans (Gal et al., 2017, 2020; Leicht-Deobald et al., 2019). Based on the phenomenological review of these organisational expectations (Alvesson & Sandberg, 2011) associated with the use of learning algorithms in people analytics, we then theorised about the perils of people analytics. Finally, we explained how the emerging perils evolve and how their negative impact on organisations and employees aggravates with each increasing maturity level of people analytics.

4.1. Theoretical implications

Our research offers two major theoretical contributions to the literature on people analytics and the field of information systems. Firstly, we introduce a fourth conceptual level of maturity, which we label autonomous analytics, to problematise the increasing technological advancement's role (Alvesson & Sandberg, 2011). The novel maturity level is based on automated decision-making, rapid progress in the field of AI, and people analytics increasingly using learning algorithms. We theorise about how this increased level of people analytics' maturity is expanding the possibilities but could also further aggravate the potential perils and negative implications of people analytics. We believe that a fourth maturity level is a useful extension of the analytical framework for scholars and practitioners in that it facilitates reflection on the use of analytics in various contexts and its implications for each level. In doing so, we advance the emerging literature on people analytics, and add to the broader stream of analytics literature. Further, we integrate the identified perils within the framework of the four levels of maturity, demonstrating how these perils evolve across the levels. While the opportunities for organisations increase with each stage of development owing to technological progress, at the same time the perils' implications for organisations, managers and employees may escalate. We therefore provide an outlook on how using more sophisticated people analytics can fundamentally change decision-making, management and human capabilities, and what this means for the future. We also show that these effects occur not only when we use AI systems or learning algorithms, but already at lower maturity levels. Because the predominant research now focuses on AI hazards, the potentially negative effects of existing technologies receive less research attention. However, these technologies remain relevant, continue to be used, and have consequences with similar kinds of risks. Thus, our study serves as a starting point to illustrate the pitfalls of less and more advanced forms of people analytics.

Secondly, we outline six potential perils of people analytics and scrutinise their far-reaching implications for organisations and employees, as well as their negative impact on decision-making, management and human skills. By unpacking the underlying assumptions, we offer a more nuanced and critical understanding of people analytics and its potential ramifications and implications. Our article extends prior systematic reviews (e.g., Fernandez & Gallardo-Gallardo, 2020; Marler & Boudreau, 2017; Tursunbayeva et al., 2018) by synthesising the particularities of people analytics and explaining why ignoring them could entail considerable risk, which in turn can lead to the emergence of potentially harmful perils. Moreover, we provide a comprehensive and holistic overview of potential pitfalls that can result from recent technological advances in people analytics. Thereby, our article goes beyond prior conceptual and empirical work that studied and theorised about only some of these potential drawbacks and did not examine them comprehensively. Further, we expand critical information systems research on the dark sides of AI by thoroughly reviewing, synthesising and integrating literature from diverse disciplines and fields, such as people analytics, business analytics, human resource management, algorithmic management, and decision-making.

4.2. Practical implications

Additionally, our paper has three practical implications for organisations and managers dealing with the implementation and use of people analytics. First, we contribute to more realistic expectations on people analytics' technologies at work by uncovering their underlying simplistic and partly misplaced assumptions. The numerous promises associated with people analytics, as well as their apparent superiority, which are further propagated by many technology vendors, can cause misguided understandings of people analytics' possibilities and an overstatement of their overall effectiveness. This can lead organisations and managers to relying on people analytics too heavily and to use them without due care, critical reflection or sufficient knowledge. Thus, we argue that the perils are not a necessary evil and inevitable consequence of using people analytics, but that they can arise from inflated expectations and might be aggravated by an unreflected use of people analytics. By exposing and mitigating the misplaced assumptions, our paper can help organisations to develop a more balanced and holistic view on the capabilities and risks of implementing people analytics. To generate realistic expectations, it is important that companies frame these assumptions in accordance with the potential risks, outlining people analytics' possibilities and limitations already when they start to implement the technologies.

Secondly, our paper raises organisations' awareness that organisations should not simply transfer other areas' analytics logic to the management and control of their employees. Avoiding due attention to people analytics' idiosyncrasies raises another critical point regarding the emergence of the perils. In this respect, our contribution offers added value for organisations, managers and employees by helping them not only to see the benefits of using people analytics, but also to be sensitised in advance to the possible negative consequences of inadequate implementation and an unreflective use of people analytics. Our study alerts organisations to possible pitfalls and draws attention to phenomena, such as emerging reductionism and self-fulfiling prophecies, and their far-reaching consequences for organisational processes, managers and. employees. Thereby, we not only raise organisations' and human decision-makers' awareness, but also contribute to a more responsible and sustainable use of people analytics, which in turn will ultimately lead to a more sustainable use of human resources in organisations.

Finally, our proposed matrix helps managers to better understand the perils arising from people analytics and to trace how these perils can evolve with increased levels of maturity. Additionally, it enables managers to attend to what is important when they use descriptive, predictive, prescriptive and autonomous analytics, and recognise the indications of the perils' emergence. Managers have a key role to play in decision-making processes and especially in technology decisions (Orlikowski, 2000). They link organisational goals and the operational staff, and therefore should be open, but at the same time also critically reflect the application of new and previously unknown technologies. Further, they should continue to believe in their own abilities, such as their intuitive judgment, reasoning and critical reflection and use people analytics to complement, not replace, their skills. Additionally, organisations should (continue to) realise that their managers and employees are their most valuable resource and recognise the need to keep the human decision-makers in the loop. Consequently, the skills managers have should not be substituted by output-oriented technologies. Instead, organisations should trust their decision-makers, give them the freedom to speak out if people analytics' decision-making recommendations go against their own insight, thus promoting an open culture of exchange and error. In order to learn from one another when dealing with new data-driven approaches and technologies (such as people analytics dashboards), we recommend a broad discourse and continuous exchange between management, HR and employees.

5. Conclusion

The increasing introduction of learning algorithms is ushering in a new era of analytics. Therefore, it is not surprising that organisations also increasingly deploy people analytics for making evidence-based decisions and managing their workforce in a data-driven approach. Based on a systematic literature review of people analytics, we have explicated five major themes in the current people analytics literature. Furthermore, to account for recent technological advances such as learning algorithms, we propose a fourth maturity level: autonomous analytics. Moreover, based on a broad theorising review of the organisational expectations associated with the use of learning algorithms and AI, we have identified six perils of people analytics. Each of the perils has profound implications for organisations and employees alike. By drawing attention to the tensions in which people analytics is embedded, our research serves as a systematic starting point for future research to shed light on the negative consequences of people analytics. The question is not whether people analytics will monitor, determine and optimise an increasing portion of our working environment in the future; rather, it is how we can reap the positive rewards this process offers, while respecting the complexity of the human condition. The use of people analytics will transform the future of work and of human decision-making. It is incumbent upon us to ensure that, through dedicated research, this future will be bright.

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