Three Issues with the State of People and Workplace Analytics

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Abstract People and workplace analytics is a hype topic. It depicts information systems and processes for data-driven decision-making that concern people-related organizational outcomes. The topic is driven by practitioners with only scarce academic backing. We outline three challenges for the field of people and workplace analytics: first, ambiguity in definitions and conceptions, second, sparse research as well as a lack of scientific evidence for the espoused value propositions, and third, a lack of strong theoretical foundation. To address these challenges, we propose a categorization schema, grounded in existing research on management information systems and tailored to people and workplace analytics. The schema helps to identify the prevalent conceptions on people and workplace analytics, and to clarify the elicited gaps in understanding.

Keywords: people and workplace analytics, issues, conceptions, categorization, state of people.

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1 Introduction

In the year 2013, the movie "Moneyball" prominently depicted data-driven people decisions in baseball. Based on the work of Billy Beane and the so-called "Sabermetrics" the trend towards analytics in sports has seen a peak in the year 2019 with the team Liverpool F.C. winning the Champions League—at least partially attributed to Ian Graham, their people analyst (Schoenfeld, 2019). At the same time, the advancement of digital technologies led to the era of big data, with a widespread adoption of analytics in various domains and business functions (McAfee & Brynjolfsson, 2012). Organisations, and in particular human resource management, see prospects for data-driven people management beyond mere reporting and controlling. Inspired by the movie "Moneyball", Ben Waber coined the term "people analytics" and popularized analytic methods that seek to scrutinize and improve people's work practices and people decisions in organisational settings (Waber, 2013). A well-known adopter of such methods is the company Uber, which makes heavy use of analytic models and nudges to influence their drivers' behaviour, e.g. persuading them to service high-demand urban areas (Möhlmann & Zalmanson, 2017).

Concomitantly, the hype surrounding people analytics is growing with newspapers, consultancies, software vendors, and influencers singing a steady and sibilant buzz alike. For introducing **people and workplace analytics**, we tentatively define it as a "*socio-technical system and associated processes that enable data-driven (or algorithmic) decision-making to improve people-related organisational outcomes*". The objective of people and workplace analytics are insights about people behaviours and prioritising data-driven (predominantly quantitative and big data, but also qualitative data) decisions over intuition (Levenson & Pillans, 2017).

In this manuscript, we address the research question how people and workplace analytics is understood and conceptualized in academia and practice. Accordingly, we briefly outline the hype and state of the people and workplace analytics field based on a literature review (cf. appendix). We discuss three challenges of the field and contribute a categorization schema to capture the diverging conceptions prevalent in the field. Subsequent research can use this schema to address the discussed challenges and advance our understanding of people and workplace analytics.

2 Hype – The Growth of People and Workplace Analytics

In 2003, Waber published his book on people analytics, spawning a plethora of publications during the last decade (Tursunbayeva et al., 2018). The increase of publications coincided with the trend towards big data and analytics. In their Harvard Business Review article McAfee and Brynjolfsson (2012) dub big data the "management revolution", while Chen et al. (2018) describe how organizations derive value from big data through business intelligence and analytics. Originating in disciplines such as marketing, sales, and finance, the investments into analytics for human resources and people related business functions are growing (Gal et al., 2017). Based on such analytics, proponents of people and workplace analytics seek insights into people-related organisational outcomes from basic metrics over performance indicators to multivariate statistical analyses (Levenson, 2018).

Driven by the available data (Davenport et al., 2010) and novel cloud capabilities (Guenole et al., 2015), 69% of enterprises with more than 10,000 employees have a people and workplace analytics team (Chakrabarti et al., 2017). People and workplace analytics is seen as a high priority by 71% of the companies (Agarwal et al., 2018) and 79% established data analyst roles for people-related business functions (Society for Human Resource Management, 2016). Stratistics MRC estimate the global market value for people and workplace analytics at USD 429 million in 2015 (Levenson & Pillans, 2017). Despite the growing interest, many organisation do not consider themselves at a mature level of people and workplace analytics operations (Levenson & Pillans, 2017).

Practitioners—vendors and consultancies in particular—put people and workplace analytics on their agenda: "*HR analytics is one of the hottest trends in the context of HR strategy and decision making. Big data in organizations is overwhelming*" (Falletta, 2014). Start-ups are founded, conferences organized (e.g. PAFOW, People Analytics and Future of Work), and expertise offered. Typical promises include the improvement of turnover, retention, recruiting, and workforce planning (Chen et al., 2018; Visier, 2018) as well as employee engagement and empowerment (Davenport et al., 2010). Beyond improving operations, proponents see the opportunity for people and workplace analytics to provide competitive advantage (Hoffmann et al., 2012) and strategic guidance (Isson & Harriott, 2016; Lawler & Boudreau, 2015). The promise of objectivity for rigorous people-related decision-making ought to give the human resources function a strategic role in the board (Fecheyr-Lippens et al., 2015).

3 Three Challenges

Despite the hype, the academic community has yet to dive deep into the topic and deliver critical guidance. As an emergent trend, we see three major issues with the state of people and workplace analytics that need to be addressed based on our literature review (cf. appendix). First, the ambiguity in terminology and definition, with authors employing varying and conflicting conceptions of people and workplace analytics, leads to an elusive understanding and blurry boundaries of the phenomenon. Second, the sparse research and a lack of scientific evidence means there is no empirical backing for many claims of positive outcomes of people and workplace analytics. Third, the current state of people and workplace analytics suffers from a weak theoretical foundation and misses an inquiry into potential side effects and unintended outcomes

3.1 Ambiguity in Terminology and Definition

In the current debate on people and workplace analytics, we find different terms used interchangeably by practitioners and academics, including but not limited to workplace analytics, people analytics, human resource analytics, and workforce intelligence, with the dominant terms being people analytics and human resource analytics in the last ten years (Tursunbayeva et al., 2018). On the one hand, different terms may subsume the same underlying conceptions; on the other hand, the same term may refer to different conceptions—ultimately leading to ambiguous use and understanding of the terms.

In the academic literature for instance, Shrivastava et al. (2018, p. 3) indicate that people analytics corresponds to human resource analytics: "*people analytics or human resource (HR) analytics refers to [...]*". Conversely, the definitions of people and workplace analytics by Cheng (2017) and by Singer et al. (2017) show conflicts. While the former states people and workplace analytics is about "*strategic influence in human resource management*" (p. 2), the latter aims at "*improving collaboration*" (p. 125) between people. Another example is that Cheng (2017, p. 2) defines people and workplace analytics as "*a tool*", whereas Marler and Boudreau (2017, p. 15) define it as "*a human resource practice*".

We find similar variation in the practitioners' literature. Guenole et al. (2015) argue that people and workplace analytics is only concerned with human resource data, processes and outcomes, while workforce (mind the different word) analytics refers to the general workforce and aims at improving performance. Sinar et al. (2018) advance a similar definition for the term people and workplace analytics that aims at the "*[...] quantification of the people drivers of business outcomes, with the purpose of making better decisions*" (p. 52).

The ambiguity of terms is exacerbated by vendors offering different services and solutions (or tools) under the same terms, e.g. one vendor may use "workplace analytics" to refer to a particular solution (e.g. Microsoft), while another vendor may use "workplace analytics" to refer to their consulting service (e.g. IBM). The underlying methodological approach and the targeted organisational outcomes vary between vendors and their services and solutions, thus, adding to the confusion. The ambiguity in terminology by academia, practitioners, and vendors mirrors the diverse landscape of definitions, and services associated with people and workplace analytics. While a clear overview is lacking, a single definition does not resolve this issue—and cannot be reasonably found. Different actors solve different problems in different contexts using the term people and workplace analytics. Hence, we suggest identifying the prevalent conceptions of people and workplace analytics to organize the field.

3.2 Sparse Research and Lack of Scientific Evidence

People and workplace analytics "*is going mainstream*" (Arellano et al., 2017, p. 1). However, the trend is criticized as being ephemeral, "*resembling a hype more than substance*" (van der Togt & Rasmussen, 2017, p. 128). The topics are being discussed without a prominent impact in the field (Rasmussen & Ulrich, 2015), suffering from consultancies and software vendors looking at commercial opportunities that provide only little value to prospective organizations (van der Togt & Rasmussen, 2017). According to Cheng (2017), this has caused organisations to engage in people and workplace analytics without an assessment of their own needs. A better understanding on what people and workplace analytics constitutes, what business problems it addresses, and how it adds value is needed (Angrave et al., 2016; Gal et al., 2017).

There is an abundance of practitioners' literature, blog entries, whitepapers, and consulting reports, as well as software vendors offering solutions for people and workplace analytics, generating a buzz in in the people and workplace analytics market with a focus on (off-the-shelf) tools, descriptive reporting and prescriptive guidelines (Angrave et al., 2016). However, the cost-benefit for these services is unclear (Cascio & Boudreau, 2011). The solutions offered are too generic, not customized, and not tailored to the specific organizational case (Angrave et al., 2016; Boudreau & Ramstad, 2007).

The paucity of scholarly work on people and workplace analytics illustrates that the academic management community has shown little importance to people and workplace analytics so far (Marler & Boudreau, 2017). However, scholars do start to take interest (Gal et al., 2017; Tursunbayeva et al., 2018) and Marler and Boudreau (2017) provide an early literature review for the human resources field. The few existing scholarly articles criticize that people and workplace analytics does not live up to its hype with many failed projects (Rasmussen & Ulrich, 2015). Empirical research is scarce and the espoused value propositions of people and workplace analytics lack scientific support (Marler & Boudreau, 2017). Side effects and unintended outcomes of people and workplace analytics are not investigated sufficiently (Gal et al., 2020). Others question the effectiveness of data-driven decision-making amidst bias and a lack of fairness, because algorithms are designed and implemented by humans (Ebrahimi et al., 2016; Zarsky, 2016). Nevertheless, it is suggested that, under the right circumstances, people and workplace analytics may have positive effects on organisational outcomes (Marler & Boudreau, 2017). For example, one empirical study by Aral et al. (2012) found a positive association between people and workplace analytics and organisational performance.

3.3 Lack of Strong Theoretical Foundation

While Tursunbayeva et al (2018) provide a scoping review across different terms and attest an increasing scholarly interest, they do not contribute to a theoretical understanding of the phenomenon. Marler and Boudreau (2017) published a literature review in the human resources field, where they primarily identified academic reviews and opinion pieces as well as practitioners' whitepapers with descriptive statistics, concluding that people and workplace analytics needs a stronger theoretical underpinning. Theoretical warrants on how people and workplace analytics generates value are lacking. Concerns regarding operationalization and measurement are not discussed. Big data or digital traces do not provide the "objective" truth that is being sought (e.g. Hüllmann & Krebber, 2020). The data is oftentimes collected without context, manipulated and shaped by the people being observed (Østerlund et al., 2020; Pachidi et al., 2016). Hence, such data—like other performance data—presupposes underlying theory to be interpreted, as well as a careful consideration of construct validity (Howison et al., 2010; Hüllmann, 2019). For example, how does trace data inform the work practices and their effectivity? Can humans be reduced to data-generating robots (Gal et al., 2020; Rahwan et al., 2019)? Such a discourse is critical for engaging with people and workplace analytics in a rigorous manner.

Conversely, the practitioners' literature is concerned with the adoption of people and workplace analytics and its drivers in organisations, as well as practical guidelines on how to establish people and workplace analytics programmes. For example, such guidelines take into account stakeholders, organisational culture, required skills, and change management (e.g. Chakrabarti et al., 2017; Guenole et al., 2015; Levenson & Pillans, 2017; Visier, 2018).

4 Categorizing Conceptions and Underlying Theory

Not everything is new about people and workplace analytics. Scientific management includes the quantification of human labour and uses statistical means to inform managerial decision-making, and the information systems discipline has extensively researched management information and decision support systems (Laudon & Laudon, 2014). We argue that research on people and workplace analytics should be informed by a synthesis of existing theories in management and information systems literature as well as adjacent disciplines. Investigating the phenomenon, the existing theories and literature shall inform perennial aspects and issues of people and workplace analytics, as well as provide guidance for future research. Reviewing and categorizing literature is fundamental in academia and helps in understanding and analysing complex topics and domains (Nickerson et al., 2013). Unpacking the prevalent conceptions, i.e. the underlying and implicit assumptions authors have in mind when discussing people and workplace analytics (Laurence & Margolis, 1999), organizes the extant knowledge and provides an overview of the field (Nickerson et al., 2013). To support such a review and categorization, we propose a categorization schema that is deduced from the three outlined challenges above. The schema is loosely inspired by Marler & Boudreau (2017) but extended and tailored to people and workplace analytics in the information systems and management community. We divide the schema into (1) "categories for conceptions", which addresses the ambiguity challenge, and into (2) "categories for underlying theory", addressing the sparse research and the lack of theoretical foundation. A preliminary test and coding of the literature showed a moderate variance per category, indicating the robustness, comprehensiveness, and explanatory power of the categories in both the practitioners and academic literature (cf. Nickerson et al., 2013). A synopsis of the schema, including examples, is available in the appendix. In the following, the category titles are highlighted in bold.

4.1 Categories for Conceptions

The **conception** specifies the underlying assumptions or thoughts, the mental representation, that the proponents of people and workplace analytics have in their mind when talking about the phenomenon (Laurence & Margolis, 1999). It typically includes "*a set of necessary and sufficient conditions*" and is crucial for organizing and categorizing knowledge (Laurence & Margolis, 1999, p. 10). Beyond the overall conception, it is helpful to break the conceptions down into their smaller constituents to address the ambiguity, as complex mental representations are formed through linking simple assumptions (Laurence & Margolis, 1999).

For examining the constituents of the conceptions, we base the categories on the dimensions of decision-making problems in the information systems discipline (Ives et al., 1980; Laudon & Laudon, 2014), because people and workplace analytics concerns decision-making. The dimensions include the primary **stakeholders**, the people responsible for driving people and workplace analytics in their organization; and the **expected outcomes** or targeted processes of people and workplace analytics. Further categories are the **methods** for performing people and workplace analytics; including the use of **information technology**; and the **type of data** being analysed (Ives et al., 1980; Laudon & Laudon, 2014).

4.2 Categories for Underlying Theory

Implied validity claims and propositions must be tested rigorously through **theoretical warrants** and evidence (Ngwenyama, 2019). The warrant is the theoretical construct (principle or rationale) through which evidence is interpreted, and depicts why and how evidence supports a particular claim (cf. Toulmin et al., 1984). In their study, Marler and Boudreau (2017), find that the majority of publications does not provide a theoretical underpinning on why and how people and workplace analytics works and produces valid and reliable outcomes. Beyond the theoretical constructs, the measurement constructs require equivalent scrutiny. How do the implemented measurements (operationalization) link to the theoretical constructs? Are the constructs coherent, valid, and reliable (Howison et al., 2010)? Quantitative data requires careful interpretation. Instead of merely counting user actions, meaning needs to be carefully ascribed and understood in the context of work (Hüllmann, 2019; Hüllmann & Krebber, 2020). Wider implications need to be considered when interpreting the data as well: people and workplace analytics adds transparency to work. Individuals understanding this transparency can engage in impression management, further skewing the reliability of insights from people and workplace analytics (Pachidi et al., 2016). Looking at artificial intelligence applications, promises of objectivity and fairness are discussed controversially. Data and decisions are not necessarily fast and unbiased (Ebrahimi et al., 2016). Data and decisions are not necessarily objective and effective (Zarsky, 2016). It depends on the humans designing the systems, the training data, and the implementation (Cowgill & Tucker, 2017).

We add the **level of analysis** as a category, because the confusion of levels between data and theoretical construct can render insights invalid (Markus & Robey, 1988). Markus and Robey (1988) distinguish individual, organization, and society levels. We add the group-level as a separate entity, as teams are a fundamental unit of the organization and a typical subject for people and workplace analytics (Hüllmann & Kroll, 2018; Levenson, 2018).

In the last category we subsume **side effects, unintended outcomes**, and relating people and workplace analytics to **existing research**, where such effects and outcomes are discussed. Do the proponents relate people and workplace analytics to management information systems or organization theory? People and workplace analytics sees the application of predictive models for the forecasting of people-related outcomes. The goal is to help managers make good decisions (Levenson, 2018). Are the changing roles of the decisions and decision-maker addressed from an information systems perspective (Berente et al., 2019)? Is people and workplace analytics another step in the development of management information systems and decision support systems? Auxiliary questions that may be addressed include the balance of management control versus empowerment of the individual. Advancing from Taylorism organization theory progressed towards seeing organizations as complex socio-technical systems (Tursunbayeva et al., 2018). How does people and workplace analytics relate to this discourse? Is it a step back towards the mechanized human (Gal et al., 2017, 2020)? The increase of transparency and information spawns concerns of privacy and workplace surveillance (Ball, 2010), as well as resistance from employees (Zarsky, 2016). Are these concerns discussed from a legislative and ethical perspective (Agarwal et al., 2018)?

5 Conclusion

People and workplace analytics is a trend emerging in practice, with a growing market that offers solutions, services, conferences and manifests itself in reports and case studies. Despite the hype, the extent of academic inquiry is lacking. Striving for a shared and theoretically sound understanding of the phenomenon, we provide a categorization schema derived from the outlined challenges of people and workplace analytics. The schema can be filled out by collecting data through interviews, surveys, or literature reviews. Since practitioners and consultancies are exposed to a variety of conceptions of people and workplace analytics, and provide a majority of the extant literature, it is worthwhile for academics to learn from them (Stockhinger & Teubner, 2018). Future research using our categorization schema will help to identify the prevalent conceptions of people and workplace analytics and clarify the elicited gaps in knowledge. Moving beyond existing reviews, the application of our schema can unravel the hidden assumptions underlying people and workplace analytics towards unifying a scattered field.

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Appendix – Categorization Schema

Categories for Conception

Term
What term is being used?
Examples: People Analytics, Workforce Analytics, Human Resources Analytics.

Conception (Overall)
What are the implicit assumptions for understanding of people and workplace analytics?
Examples: Understood as a process/approach, or a software tool.

Information technology / Data sources
Does the conception consider information technology important to reach the goals? What data sources are collected and analysed?
Examples: IT as an enabler; Dashboards for visualization / Big data; Surveys

Methods
What are the methods being used?
Examples: Multivariate statistics; Qualitative analysis.

Stakeholders
Who is responsible and drives the topic?
Examples: Human resources; General management.

Outcomes
What is the main outcome, goal, or purpose?
Examples: Improve human resources processes (e.g. retention, hiring, talent development); improve people-related organisational outcomes more generally.

Categories for Underlying Theory

Underlying theoretical warrants / theoretical framework / epistemology
What underlying warrant, i.e. the logic, epistemological view, or theory, is implied when talking about people and workplace analytics and its outcomes?
Examples: How well can people data capture humans and lead to meaningful insights? What theory is used for interpretation of measurements?

Level of analysis
Which level of analysis is depicted?
Examples: Individual, group, or organisational level.

Side effects / Unintended Outcomes / Existing Research
What areas with an influence of or on the topic are addressed?
Examples: Ethics, privacy, surveillance, taylorism, laws, regulations, resistance, adoption, behavioural change, impression management, management information systems.

Appendix – Literature Review

We conduct a literature review across academic and practitioners' literature, because scientific research is scarce, while practitioners' and consultancies are driving the topic of people and workplace analytics. To identify relevant literature, we first search the academic databases SCOPUS and Web of Science. Second, we perform backwards and forward search, including references to practitioners' literature. Beyond the literature from the search, we included references that were brought to our attention on social media, or at conferences.

Keywords:

- People Analytics
- HR/Human Resources Analytics
- Workplace Analytics
- Workforce Analytics
- Social Analytics

Search Criteria:

- Title
- Abstract
- Keywords