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RESEARCH PAPER

# Driving business value through people analytics: Literature review and research agenda from an information systems perspective

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## Abstract

People analytics has evolved as an evidence-based approach to human resource management (HRM) that uses technology to analyze employee-related data with the aim of improving HRM and overall business performance. Despite its potential, people analytics maturity remains limited in many firms. The information systems (IS) discipline with its dual lens at the intersection of technology and management is particularly well-positioned to help advance the field. The purpose of this paper is to support future research and managerial action by means of a research agenda as well as an integrative framework of people analytics with a focus on business value creation. These contributions are grounded in the results of a systematic literature review of 122 research papers from the IS discipline and—for overall context—a bibliometric analysis of 1,682 research papers spanning IS and other disciplines. We find that people analytics research in a wider sense has existed since the 1960s and is divided into a predominantly technological and a predominantly managerial stream. By developing new people analytics approaches and identifying enabling factors for implementation, IS researchers have begun to help bridge this divide. However, there is still a need for further IS research, which can be guided by our research agenda and integrative framework, encompassing HRM, data/technology, and employees as the key resources whose development and alignment are essential for creating business value through people analytics.

**Keywords** People analytics · Human resource analytics · Human resource management (HRM) · Business value creation · Integrative framework

**JEL classification** M00

## Introduction

Interactions of organizations with their employees are increasingly characterized by digital platforms, such as automated job matching, application and hiring systems (Hofeditz et al., 2022; Tran Nhat et al., 2024), artificial intelligence (AI)-based support and collaboration tools (Mirbabaie et al., 2022; Pillai et al., 2024), e-learning platforms (Almgerbi et al., 2022; Tao Li et al., 2024), and enterprise social networks (Esmaeili & Zantedeschi, 2022; Schötteler et al., 2023). As these technologies evolve, they generate and accumulate vast amounts of employee-related data across systems—reflecting the increasing datafication of organizations (Teebken et al, 2025). Advanced analysis of this data—referred to as people analytics—creates ample opportunities to enhance human resource management (HRM) activities (Okatta et al., 2024; Ulrich & Dulebohn, 2015; van den Heuvel & Bondarouk, 2017) with the ultimate goal of improving HRM and overall organizational performance. Some success stories showcase an 80% increase in recruiting efficiency or a 25% increase in business productivity (McKinsey & Company, 2023). But despite these opportunities, people analytics has not yet fully unleashed its alleged potential to create value from data. For about a decade,

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the average effectiveness of respective human resource (HR) analytics systems has stagnated (Lawler & Boudreau, 2018, 2020). Recent surveys find that maturity and sophistication levels of people analytics tend to be low in most organizations: many have not yet developed capabilities beyond simple reporting (Decker et al., 2023) and take narrow approaches to data analysis (Leonardi & Contractor, 2018). Consequently, the practice eventually "hits a wall" (Boudreau & Ramstad, 2007, p. 189) and people analytics is at risk of becoming yet another "management fad" (Rasmussen & Ulrich, 2015, p. 236). In academia, three main shortcomings of the field are primarily discussed. First, innovative well-grounded examples of concrete people analytics approaches are scarce (Cheng & Hackett, 2021; Edwards et al., 2022; Tursunbayeva et al., 2018). Second, the connection between people analytics and concrete business problems as well as organizational outcomes is not sufficiently established (Ben-Gal, 2019; Larsson & Edwards, 2022; Rasmussen & Ulrich, 2015). Third, many issues of organizational readiness for people analytics remain unsolved, including ethical concerns (Gal et al., 2020; Klöpper, 2023; Köchling et al., 2021), a gap of skills and knowledge (Angrave et al., 2016; Jiang & Akdere, 2022; Ongena et al., 2024), and a lack of suitable organizational processes (Füller et al., 2022; McIver et al., 2018; Someh et al., 2023).

As it enables the application of information technology (IT) for managerial and organizational benefit (Hevner & March, 2003), the information systems (IS) discipline is particularly qualified to help address these shortcomings—eventually fostering business value creation through people analytics. Effectively, the shortcomings represent key elements of what Benbasat and Zmud (2003) describe as the core of IS research, namely an IT artifact (people analytics approaches), its usage and impact (link to business problem and outcomes), as well as the practices and capabilities involved in the implementation of the artifact (organizational readiness). For IS to make significant contributions, intertextual coherence of existing knowledge is a necessary prerequisite (Locke & Golden-Biddle, 1997). However, the field of people analytics is dominated by largely incoherent bodies of literature fragmented both within IS and across disciplines. We observe the use of different terms and definitions as well as limited concurrence of technological and managerial perspectives in existing literature. Hence, not only is there an academic-practitioner gap as observed by McCartney and Fu (2022b) but also a divide between different research (sub-)areas. This fragmentation also indicates a theoretical gap, as most existing studies fail to integrate perspectives into a unified understanding of people analytics as a socio-technical phenomenon. A literature review is suitable to bridge this gap by providing a coherent foundation for future research. While literature reviews exist that focus on specific aspects of people analytics (see background and related work), to the best of our knowledge, a comprehensive literature review on people analytics in IS research—as we present in this work—is missing. The goal of this paper is to provide a solid foundation for future knowledge generation in IS (Webster & Watson, 2002) by addressing critical knowledge gaps (Rowe, 2014). We hence aim to answer the following research questions:

- **RQ1.** What research streams have evolved in people analytics across disciplines over the past decades?
- **RQ2.** What are the focus areas and hence the contributions of the IS discipline regarding people analytics?
- **RQ3.** What are potential future research areas on people analytics in the IS discipline?

Our approach to address these questions is twofold. For the cross-disciplinary perspective (RQ1), we conduct a bibliometric analysis of 1,682 papers published in the past decades. This allows us to capture the development of the people analytics field over time and lays the foundation for understanding how the IS discipline can help advance the field. For the IS perspective (RQ2 and RQ3), we undertake a systematic literature review of 122 papers from IS outlets. We identify nine research foci with regards to people analytics approaches and seven enablers for people analytics implementation. The synthesis of these findings yields two important contributions to advance the people analytics field: we derive (1) an agenda for future IS research, which is supported by (2) an integrative framework of business value creation through people analytics that helps contextualize future research as well managerial action on people analytics.

Our paper is structured as follows: first, we define people analytics and provide an overview of related work. Second, we introduce the methodological basis. Third, the results of the cross-disciplinary bibliometric analysis and the IS-specific structured literature review are presented. In conclusion, we synthesize our findings to propose an integrative framework and derive a research agenda, before we discuss implications and limitations.

## Background and related work

Recent advances in fields such as big data analytics (Hamilton & Sodeman, 2020), machine learning (Garg et al., 2022), and AI as a whole (Vrontis et al., 2022) have created expectations for data-centric, technology-driven approaches that enhance HRM work. In this context, people analytics is widely deemed a recent innovation. However, there is a rich research tradition around measurement and quantitative analysis for HR spanning multiple decades—a fact that is often overlooked in current literature. Early approaches to value HR (*HR Accounting*) date back to the 1960s. During this time period, accounting scholars developed initial models to better represent the value of a firm's employees in its financial reporting (Hermanson, 1964) and organizational psychologists sought to advance theories of personnel "attitudes, loyalties, (…), and similar kinds of intervening variables" (Likert, 1967, p. 105) as quantifiable factors of firm productivity. Fitz-enz (1978, 1984) was among the first to argue specifically from an HRM perspective that there was a need in applying consistent forms of measurement if HR departments were to take on a more strategic role in organizations. During this paradigm shift, from the traditional view of HRM as mere personnel administration to strategic HRM (playing a key role in driving business value), the model of HR as a business partner (Ulrich, 1997) has been highly influential and widely adopted. Complementing qualitative with quantitative perspectives is one key enabler, so that in an updated version of the model, Ulrich et al. (2017) describe analytics as an integral capability of effective HRM departments. This evolution is closely intertwined with the technological development of human resource information systems. With the emergence of client–server-based applications from the 1980s onwards, the analysis of HR-related data was made available to larger audiences and ever since, these systems have developed at an increasing pace (Johnson et al., 2016).

The term people analytics however has gained popularity only in the early 2000s, e.g., with Google's introduction of a respectively named department (Garvin, 2013). But both researchers and practitioners have used multiple terms interchangeably to convey the meaning of people analytics. These include *HR analytics* (Bassi, 2011; Fitz-enz, 2010; Ulrich & Dulebohn, 2015), *HR metrics* (Carlson & Kavanagh, 2012; Durai et al., 2019; Lawler et al., 2004), *workforce analytics* (Hota & Ghosh, 2013; Huselid, 2018; McIver et al., 2018), *talent analytics* (Davenport et al., 2010; Nocker & Sena, 2019; Sivathanu & Pillai, 2020), and *human capital analytics* (Boudreau & Cascio, 2017; Levenson & Fink, 2017; Schiemann et al., 2018). Despite their variety, these terms have only led to limited definitory differentiation, as they represent—at least in parts—a "re-branding of similar concepts by successive practitioner cohorts and vendors, as they seek to differentiate their knowledge, services, or products" (Tursunbayeva et al., 2018, p. 230), which have found their way into the academic literature. Not least because of its popularity and the relative semantic breadth of the word people versus terms such as talent or human capital, people analytics can reasonably be used as an umbrella term—and we do so in this paper. Broadly, three different types of people analytics definitions exist: first, researchers with a primarily technological lens describe it as a *socio-technical support system for HR involving analytics tools and processes* (Gal et al., 2017; Gelbard et al., 2018; Hüllmann & Mattern, 2020; Sharma & Sharma, 2017; Shet et al., 2021). These researchers tend to focus on the aspect of applying the latest disruptive technology, such as AI. Second, authors with a primarily managerial lens describe people analytics as an *approach to making better HRM decisions based on evidence in the form of quantitative data* (Claus, 2019; King, 2016; McIver et al., 2018; Rasmussen & Ulrich, 2015; Ulrich & Dulebohn, 2015; van der Togt & Rasmussen, 2017). These researchers tend to also consider less sophisticated forms of data analyses. Third, some authors have reconciled the technological and managerial lenses and describe people analytics as a *novel, technology-enabled, data- and analytics-driven form of decision-making in HRM to drive business impact* (Ben-Gal, 2019; Giermindl et al., 2022; Margherita, 2022; Marler & Boudreau, 2017; Tursunbayeva et al., 2018). However, the third lens implies that people analytics is a completely new field and hence overlooks its history. This may lead to incomplete research perspectives, e.g., by overlooking important contextual factors, which can hinder knowledge accumulation, and eventually harm progress in the field—or as Land (2010, p. 386) puts it, IS research on "even the most transformative, revolutionary innovations benefits from the study of the historical context." Therefore, in line with other authors such as Bassi (2011) or Coron (2022), we advocate for an understanding of people analytics that focuses on the broad underlying concept of quantitative analysis in HR and thereby recognizes its historical evolution. Accordingly, we define people analytics as *an evidence-based approach to HRM that uses technology to analyze data related to existing, former, and prospective employees across all HRM practices with the ultimate goal of improving HR and overall business performance*.

In recent years, several literature reviews aimed to consolidate people analytics research from three main perspectives. First, a majority of researchers aim to contribute to the ongoing debate on how to conceptualize people analytics by discussing aspects such as existing practices, underlying mechanisms, value proposition, and outcomes (Alvarez-Gutiérrez et al., 2022; Coolen et al., 2023; Margherita, 2022; Marler & Boudreau, 2017; Tursunbayeva et al., 2018). For example, Marler and Boudreau (2017) dissect people analytics as an HR innovation and identify a need for more high-quality research delivering empirical evidence. Second, another set of literature reviews focuses on barriers for people analytics adoption and discusses the risks that it entails (Angrave et al., 2016; Coron, 2022; Giermindl et al., 2022; Levenson & Fink, 2017; McCartney & Fu, 2022b). For example, Coron (2022) notices a lack of analytical skills among HR professionals and Giermindl et al. (2022) summarize six perils of people analytics, such as a potential marginalization of human decision-making. Third, another group of researchers address the technological and analytical advances that allow for increasingly sophisticated forms of people analytics, e.g., by leveraging AI (Charlwood & Guenole, 2022; Gélinas et al., 2022; Prikshat et al., 2023; Qamar et al., 2021; Zhang et al., 2021). Although people analytics might seem to be a well-reviewed field, neither any individual review nor the reviews collectively have yet addressed the research questions we pose. On the one hand, existing reviews typically do not acknowledge the breadth and historical evolution of the field—although scientifically relevant (see RQ1). On the other hand, no systematic review of IS literature on people analytics exists to date—although the discipline is particularly qualified to address the field's research gaps (see RQ2 and RQ3).

## Review methodology

For IS researchers to make contributions to the field, intertextual coherence of existing IS knowledge is a prerequisite (Locke & Golden-Biddle, 1997). Such intertextual coherence is yet to be achieved for the field of people analytics through a review of IS literature, in which existing knowledge is reviewed, critiqued, and synthesized—and new knowledge is created in the form of a research agenda and a conceptual framework that advances beyond existing models (Post et al., 2020; Torraco, 2016). Therefore, we conduct a systematic literature review as proposed by Webster and Watson (2002). At the same time, we acknowledge that over the last decades, people analytics has developed as a broad field across disciplines. Hence, in addition, a holistic view of the field's evolution is necessary to help overcome its fragmentation and establish a frame of reference for future IS research. For this purpose, we conduct a bibliometric analysis, which is suited to "unpack the evolutionary nuances of a specific field" (Donthu et al., 2021, p. 285). With this combined approach of a systematic literature review enriched by a bibliometric analysis, we follow recent examples of Electronic Markets papers that have employed bibliometric analysis (Liu et al., 2020; Zhang et al., 2023), systematic literature reviews (Akter & Wamba, 2016; Baethge et al., 2016; Brasse et al., 2023), or a combination of both (Bawack et al., 2022), similar to our approach.

### Bibliometric analysis

The bibliometric analysis entails the following steps adapted from Donthu et al. (2021): definition of aims and scope (already discussed above); selection of bibliometric technique, collection of data, and conduction of the analysis (all three discussed in this section); and interpretation of the findings (discussed in the results section).

#### Technique selection

Science mapping is an established form of bibliometric analysis to determine the research foci and structural evolution of a field. It relies on measures of relationship between different works based on paper content or metadata to identify subdomains in the field, i.e., clusters of articles (Noyons et al., 1999). Co-word analysis is used to calculate textual similarity of articles' titles, abstracts, and keywords or full texts. Co-citation analysis and bibliographic coupling are the most common metadata analyses and serve to identify which papers are cited by the same source or which papers cite similar sources respectively (Zupic & Cater, 2015). Bibliographic coupling has been shown to deliver more coherent clusters of papers and can be further enhanced by combining it with co-word analysis into a hybrid measure (Boyack & Klavans, 2010). We therefore follow the approach by Meyer-Brötz et al. (2018), which relies on a hybrid similarity measure and uses hierarchical clustering (Louvain algorithm) to group papers into thematic clusters, before the network is visualized using the Fruchterman-Reingold algorithm.

#### Data collection

We use two search queries—one with a traditional and the other with a contemporary focus (see Fig. 1). The traditional query contains the older terms *HR accounting* and *HR metrics*. The contemporary query comprises the current terms *people analytics*, *HR analytics*, *workforce analytics*, *talent analytics*, and *human capital analytics*. However, based on the related work and our definition of people analytics, we expect that these keywords will not capture the entirety of scientific literature on people analytics. We therefore also combine the term HR with the names of the most common approaches of quantitative analysis from the past and present. *Utility analysis* and *scorecard* are included as traditional methods (Rasmussen & Ulrich, 2015). Modern analytics methods are performed with algorithms from data science. Hence, we add the word *algorithm* and the most common data science fields, i.e., *big data*, *AI*, *machine learning*, and *data mining* (Emmert-Streib & Dehmer, 2019), in combination with *human resources*. These queries represent the basis for a database search on title, keywords, and abstract.

Major databases commonly used in bibliometric studies for their breadth of coverage are Web of Science, Scopus, and Google Scholar. They exhibit individual strengths and weaknesses with regards to data quality. Google Scholar tends to apply a very broad definition of what is considered scientific (versus grey) literature and to suffer from inaccurate metadata (De Winter et al., 2014). While Web of

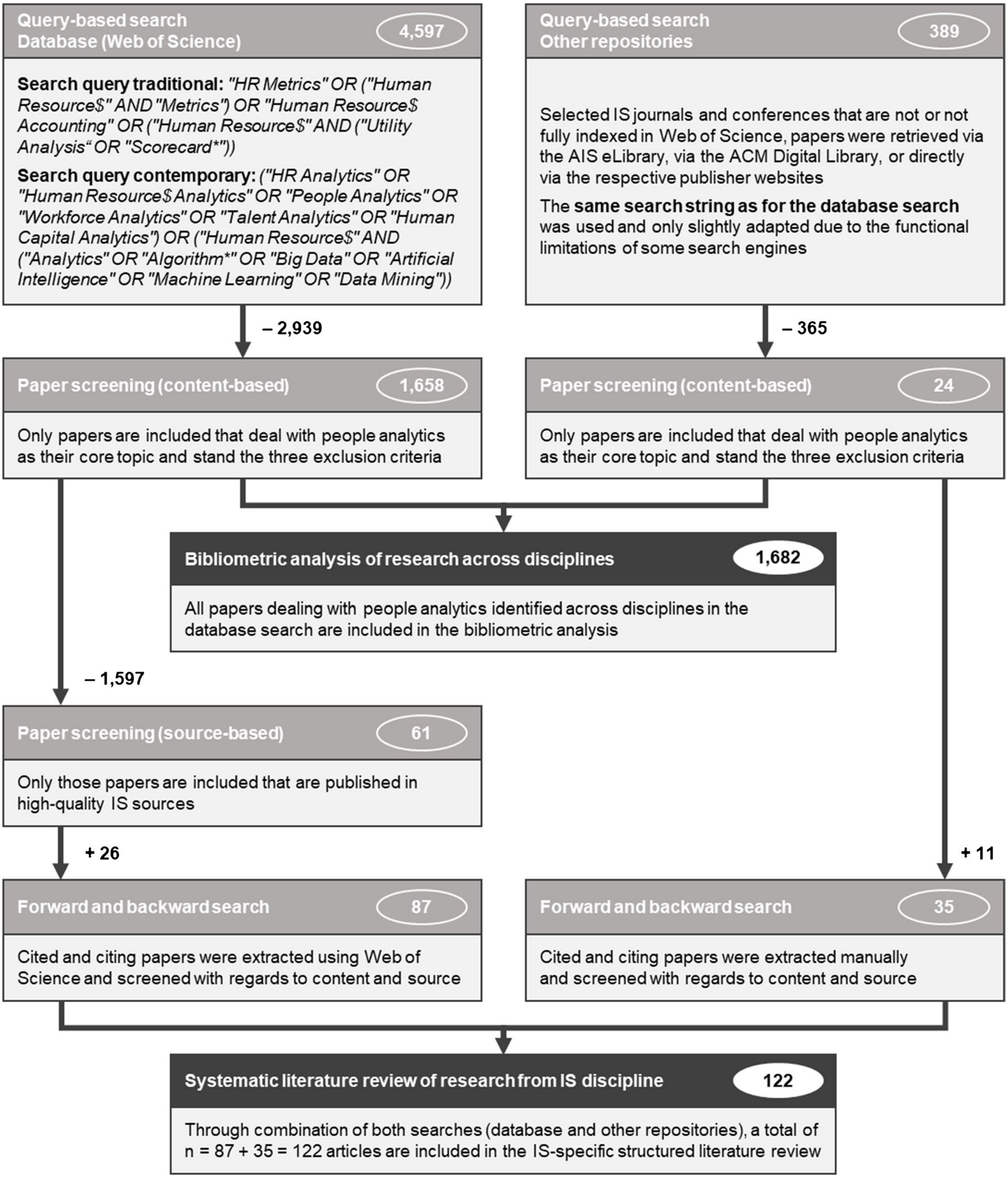


**Fig. 1** Overview of literature search and screening

Science and Scopus are reported to have similar levels of database mapping errors overall, Scopus tends to suffer more from duplicated citation records (Valderrama-Zurián et al., 2015) and missing articles from sources that are indexed (Franceschini et al., 2016), which is particularly relevant for broad reviews and bibliometric studies like ours. Hence, for our study, we use extracts from Web of Science. 4,597 unique datasets were retrieved across disciplines, out of which 1,682 papers[1] deal with people analytics as their core topic and hence are included in our bibliometric analysis (see Fig. 1, procedure of manual screening process detailed below).

### Analysis conduction

Based on this dataset, we initially conduct a trend momentum analysis for the papers captured by each component of our search strings as proposed by Lu and Yang (2012). This allows us to demarcate time periods that reasonably approximate the evolutionary stages of the field in a temporal sense (see Fig. 4). We then apply the bibliometric technique by Meyer-Brötz et al. (2018) as outlined above. First, we identify level-one clusters of papers within each time period to qualify it. Second, the level-one clusters' connections and their intensity are calculated across time periods (i.e., the similarity value for each pair of clusters in adjacent periods) to reveal streams of research over time. Third, subclusters are identified in each level-one cluster to better understand its cognitive structure. Fourth, each research stream and its constituent clusters are interpreted and titled by reviewing their keywords (i.e., the words most commonly used as identified in the co-word analysis) and screening the content of the papers included. For the configuration of the algorithms used, we adhered to the common practice in bibliometric analysis of heuristically deriving suitable parameter values (Meyer-Brötz et al., 2018).

## Systematic literature review

The quality of any literature review stands and falls with the rigor of its literature selection and analysis process. Therefore, we follow a structured approach in the style of vom Brocke et al. (2009), which entails source selection, query-based search, forward-/backward search, paper screening, and literature analysis/synthesis.

### Source selection

To identify high-quality research, rankings are helpful (Levy & Ellis, 2006; vom Brocke et al., 2009). We include the leading outlets with IS focus from three major journal rankings, namely VHB Publication Media Rating, Academic Journal Guide, and ABDC Journal Quality List. We consider the top two categories for the ABDC ranking that applies a four-point scale and the top three categories for the other two rankings which apply a five-point scale. This leads to a selection of the leading 20–35% of journals relevant to IS per ranking. Additionally, to ensure a holistic coverage of high-quality, peer-reviewed research in the IS discipline, we reconcile the resulting selection with the list of journals and conference proceedings published by or affiliated with the Association for Information Systems (AIS) and those recommended by the AIS special interest groups. In total, 124 IS outlets (107 journals and 17 conferences) are in scope for our review.

### Query-based search

As explained in the context of the bibliometric analysis, our literature search is based on two search queries—a traditional and a contemporary one (see Fig. 1)—and is conducted on title, keywords, and abstract using the Web of Science database. For the systematic literature review, we additionally retrieve papers from selected IS journals and conferences that are not fully indexed in Web of Science from other repositories, such as the AIS eLibrary, the ACM Digital Library, and publisher websites. A total of 4,986 papers were identified for screening.

### Paper screening

Papers were manually screened based on their content and included only if their core topic is people analytics. The screening process was conducted by three researchers. Each researcher first reviewed the title, followed by the abstract and keywords, and—if the relevance to the core topic of people analytics remained unclear based on the exclusion criteria—proceeded to full-text screening. We applied three exclusion criteria. (1) Formal considerations: papers were excluded if they represent non-scientific research, book reviews, or retracted articles. (2) No, or only tangential, connection to people analytics: papers were excluded if they do not primarily treat the concept of people analytics as per our definition. Examples are works that deal with the ability of HR to accommodate changing needs of an organization due to technological advances (e.g., non-analytics-related changes in recruiting to hire AI-proficient talent) but not the usage of analytics in HR itself, works that exclusively discuss enabling technologies for modern HRM (e.g., cloud-computing environments) but not analytics that can be performed based on these technologies, and works that treat the implementation of analytics in organizations in general (e.g., process analytics) without a clear link to HR-related data or HRM practices. (3) Analytics only used as a method of empirical research: papers were excluded if they entail analyses that could potentially be considered people analytics but are performed solely for scientific concept or theory validation and hence would not likely be replicated by practitioners in an organizational context.

[1] This figure also reflects the exclusion of 76 papers which appeared in special issues of scientific journals published by Hindawi (part of Wiley) in 2021 and 2022, which were subject to publication manipulation at scale, resulting in retraction of hundreds of articles as they failed to meet scientific standards (van Noorden, 2023).

For example, Sun and Shang (2014) collect and analyze data from employees to test their model of intraorganizational social media use with regards to different forms of social capital. While the researchers perform analytics with people-related data, their work is foundational in nature and lacks a connection to HRM. These criteria are the result of an iterative process, in which three researchers coded a randomly selected 10% sample of the initial search results in small tranches and kept refining the code-book by discussing their disagreements.

By utilizing such an iterative approach, we were able to increase interrater reliability (IRR) as measured by Cohen's Kappa from an initial 0.69 in the first sample tranche to 0.85 for the remaining 90% of papers, leading to an overall IRR of 0.83, i.e., we went from a "substantial" to an "almost perfect" strength of agreement (Landis & Koch, 1977, p. 165). In total, we excluded 2,939 papers based on title, abstract, keywords, and full-text screening from the query-based search in Web of Science. Additionally, 365 papers were excluded from those found in selected IS journals and conferences that are not, or not fully, indexed in Web of Science. After further exclusion of those papers from the Web of Science search that were not published in high-quality IS sources, the process resulted in the inclusion of 61 + 24 = 85 papers.

## Forward/backward search

Based on these 85 papers, we also conducted forward and backward reference searches (Levy & Ellis, 2006) to identify relevant literature that preceded (cited articles) or succeeded (citing articles) the papers from the initial searches. For papers found through Web of Science, we used the database's functionality to retrieve cited as well as citing articles. For articles retrieved from other IS-specific repositories, the process was conducted manually using the bibliographies of each article. Papers were considered if they appeared in one of the 124 IS outlets in scope. Then, the same content-based screening process as presented above was conducted, resulting in a total of 122 papers identified for inclusion in the IS-specific systematic literature review. For the forward and backward search, the interrater reliability as measured by Cohen's Kappa increased to 0.88.

## Literature analysis/synthesis

For the analysis of the selected articles, we first adapt a concept matrix from Salipante et al. (1982). To take into account the nature of people analytics as a field located at the intersection of technology-supported data analysis and HRM, we augment the approach by using two (instead of one) conceptual dimensions (see Fig. 2). On the one hand, we consider the major *HRM practices* and their goal to support and enhance company performance (Noe et al., 2017). On the other hand, we use the well-established classification of *data analysis approaches* into descriptive, predictive, and prescriptive analytics (Sivarajah et al., 2017). Furthermore, to gain deeper insight into the *types of analytical methods* used, we apply a methods taxonomy based on Lepenioti et al. (2020) and Liyanagamage and Fernando (2023). However, not all papers focus on specific people analytics approaches but rather different types of *enablers* for people analytics. We analyze these works using open coding known from grounded theory (Strauss, 1987). All articles are coded by two researchers. The IRR as measured by Cohen's Kappa was 0.92, which is considered an "almost perfect" strength of agreement (Landis & Koch, 1977, p. 165).

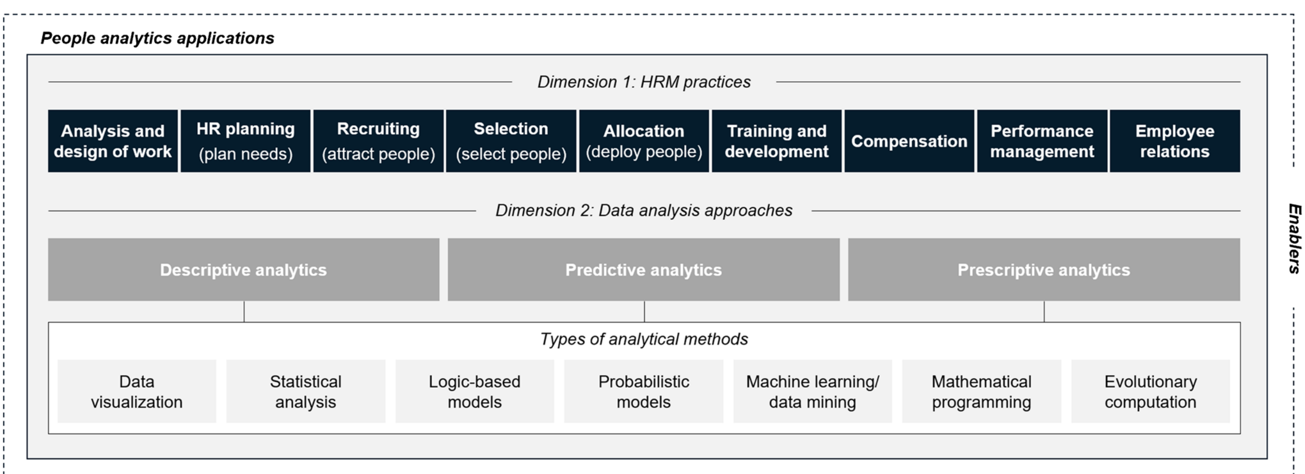


**Fig. 2** Analysis scheme

## Results of bibliometric analysis: People analytics research streams across disciplines

With regards to RQ1, we can state most fundamentally that researchers have investigated the field of quantification and measurement in HR for decades. However, the interest in people analytics has experienced massive growth over the last decade (see Fig. 3). While global academic publishing activity increased by 4.7% p.a. between 2010 and 2022 (National Science Board, 2023), people analytics research output grew about three times that fast.

The particular upsurge after 2020 is mainly driven by an increased interest given the forced workplace changes during the COVID-19 pandemic (e.g., ca. 10% of articles mention the pandemic in title or abstract in 2022). Prior to the year 2000, articles stem nearly exclusively from the traditional search query (HR metrics, HR accounting, etc.) with the number of publications remaining on a relatively low and stable level over time. After the turn of the millennial, the field is clearly dominated by works on contemporary concepts (HR analytics, HR and AI, etc.).

To better understand the thematic dynamics, we compared the trend momentum (Lu & Yang, 2012) of the terms included in our contemporary search query. As illustrated in Fig. 4, the topic of algorithms in HR gains momentum in 2006 and also the traditional stream of research is revitalized. It is not until 2013 that new terminology (people analytics, HR analytics, etc.) begins to be used more widely. At this point, the number of papers per year is already considerably higher than before 2000, but experiences another substantial increase after 2018, when the topics ML and AI in HR gain momentum.

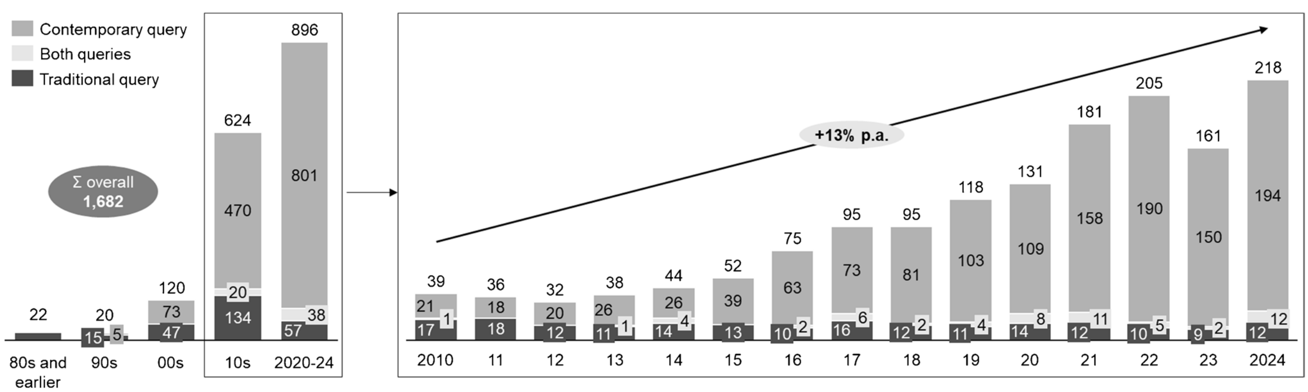


**Fig. 3** Number of articles by year

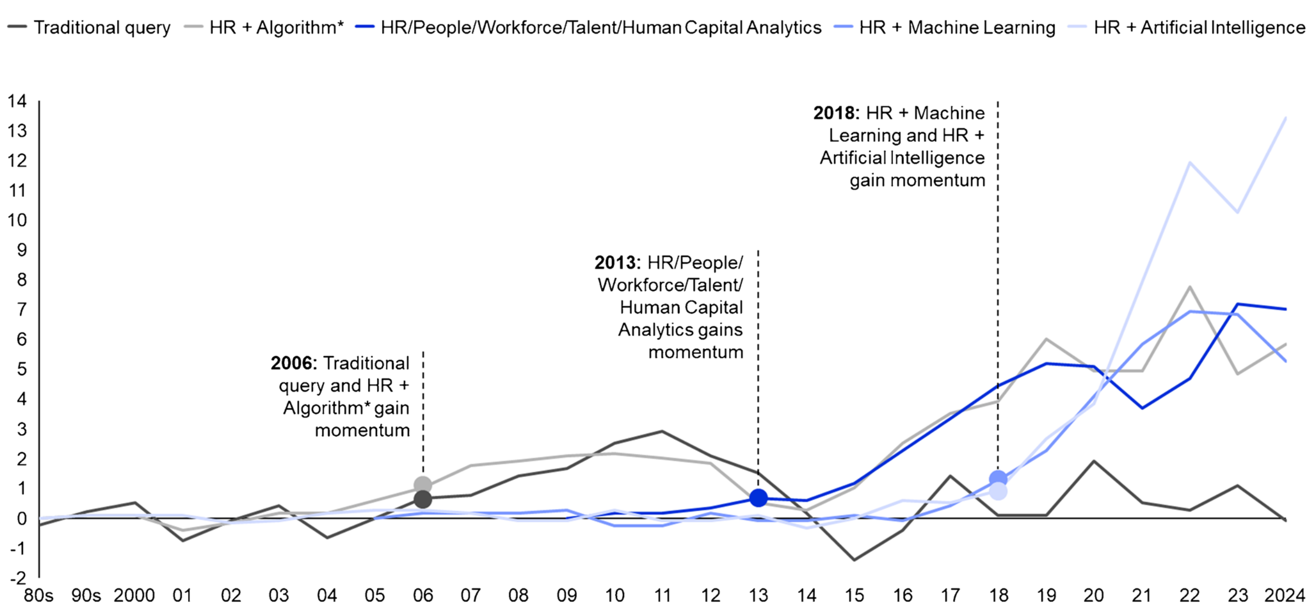


**Fig. 4** Trend momentum analysis of search terms

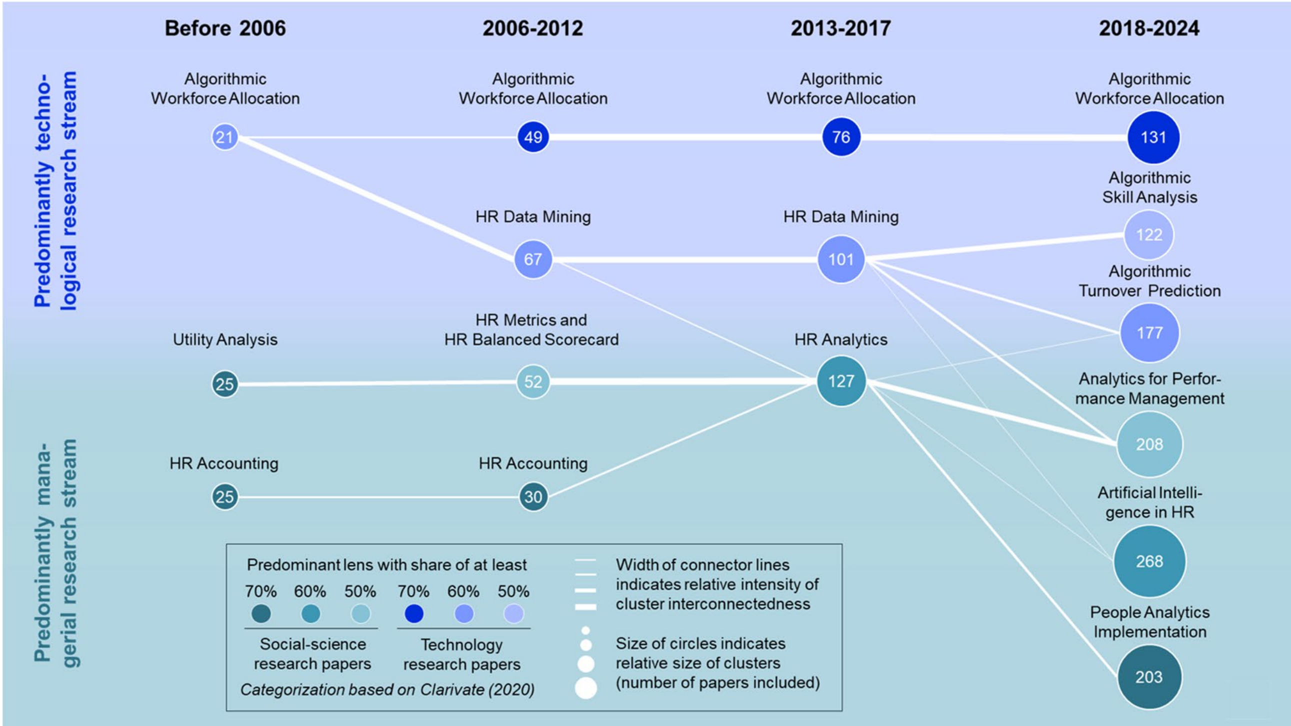


**Fig. 5** Development of people analytics research streams over time

From these observations, we derive four time periods to structure our analysis (see Fig. 5). Across these time periods, our science mapping reveals a total of 16 content clusters, which fall into two major research streams that exhibit limited interconnectedness. One stream predominantly includes papers from management research outlets, which in large parts discuss people analytics from a conceptual and organizational point of view. The other stream mainly includes papers from technology-oriented sources with a focus on the development, refinement, and evaluation of algorithmic models.

## Historical evolution (pre-2018): Two distinct research streams emerge

In the predominantly managerial research stream, early conceptualizations of what we call people analytics today date back to the 1960s, when researchers such as Likert and Bowers (1969, p. 588) argued that "financial performance records (…) contain serious inadequacies (…) as long as human resources are ignored." With *HR accounting*, accounting scholars sought to reflect employees as a human asset on the balance sheet (Hermanson, 1964) and provide a support tool for management decision-making (Brummet et al., 1968). In the late 1990s and early 2000s, developed economies experienced a change toward what Drucker (1969) had called a knowledge economy. New questions about how to value human capital were raised and—following the groundwork of Flamholtz (1999) and others—researchers sought to revive HR accounting. They aimed to link newly conceptualized human capital and related interventions, such as initiatives for work-life-balance or employee well-being (Morris et al., 2009; Roslender et al., 2009), to financial firm performance (Cohen & Kaimenakis, 2007; Crook et al., 2011). However, given their alleged complexity and persistent objections from the accounting profession, HR accounting applications remained rare in practice (Roslender & Stevenson, 2009).

With the gradual emancipation of HR to a strategic business partner in organizations (Ulrich, 1997) came calls for a "rigorous measurement mind-set" in what was deemed "often inexact" (Gandossy & Guarnieri, 2008, p. 65) people-related processes. The foundation had been laid by *utility analysis* (Shultz, 1996), a tool to evaluate different courses of HRM action and report their impact (however not as a holistic accounting figure reported on the balance sheet). It uses mathematical models to compute the value of HRM programs within and across employee cohorts (Boudreau, 1983)—such as for personnel selection (Cascio & Silbey, 1979; Cronshaw & Alexander, 1985; Schmidt & Hunter, 1998), performance evaluation (Florin-Thuma & Boudreau, 1987; Landy et al., 1982), or training and development (Cascio, 1982; Mathieu & Leonard, 1987). Over time, the concept of *HR metrics* gained popularity, i.e., the application of management control systems in HR (Gates & Langevin, 2010; Petroulas et al., 2010), which comprise financial and non-financial performance indicators that logically link to a cascade of business goals (Fitz-enz & Davison, 2002). Particularly, it was the *Balanced Scorecard*, in its general form introduced by Kaplan and Norton (1992), that emerged as a common tool in HR as well. After Becker et al. (2001) had proposed an adaptation of the Balanced Scorecard to measure HRM performance, numerous researchers followed with suggestions for refinements considering employee engagement (Rampersad, 2008), safety and health (Köper et al., 2009), or compensation (Snapka & Copikova, 2011). Other researchers investigated the application of the HR Balanced Scorecard in different settings, such as the public sector (Cunningham & Kempling, 2011), the healthcare industry (Fottler et al., 2006), or organizational transformations (Tsasis & Harber, 2008).

With the rising relevance of big data, the understanding advanced in organizations that existing metrics would need to evolve (Chen et al., 2012; Davenport, 2006). Specifically, HR practitioners started to see transformative potential in *HR analytics*[2] (Angrave et al., 2016). Fueled by success stories from companies like Google (Garvin, 2013) and calls from management consultants (Mankins et al., 2014; Pape, 2016), organizations started to move from descriptive metrics based on past data to future-oriented predictive analytics (Fitz-enz & Mattox, 2014). From the wide array of operational and strategic HR decisions that were now expected to become more evidence-based (Dulebohn & Johnson, 2013), a variety of contemporary terms developed (people analytics, talent analytics, etc.). Researchers addressed topics such as improvements to strategic workforce planning (Lu et al., 2014; Sayadi et al., 2017; Weiss, 2016), enhanced practices for employee skill (Bassi & McMurrer, 2016) and performance management (Sharma & Sharma, 2017), as well as (again) their link to firm performance (Bourne et al., 2013; Tregaskis et al., 2013; Vugalter & Even, 2015). Another main area of research deals with the organizational implications of HR analytics, such as employees' perceptions (Khan & Tang, 2016), success factors (Green, 2017), and the impact on HRM decision-making (Dias & Sousa, 2015).

While the previously discussed works mainly stem from fields such as accounting, organizational psychology, and management science, another, predominantly technological, stream of research developed in computer science and operations research. Within this stream, *algorithmic workforce allocation* seeks to establish decision support systems for questions such as which employees are suited best to be placed where, in which role, and when. Some researchers built on fuzzy set theory (Zadeh, 1965) while other early approaches include the usage of genetic algorithms for the optimization of work timetables, crew schedules, or set-up of assembly lines (Celano et al., 2004; Kragelund, 1997) as well as the application of rule-based expert systems for internal personnel selection (Hooper et al., 1998). By the early 2000s, algorithmic solutions to the optimization problem of workforce allocation had become a steady stream of research with constantly refined approaches. Problem formulations have become significantly more complex, now requiring multi-objective optimizations that address multi-period (Delgoshaei et al., 2017), multi-project (Gutiérrez et al., 2016), and multi-skill (Chen et al., 2017) contexts.

During the 2000s, companies started to use *HR data mining*, i.e., apply data mining approaches to HR contexts. Given their high practical relevance and cost implications (Navarra, 2022; Tziner & Birati, 1996), the practices of recruiting, selecting, and retaining employees emerged as highly relevant applications. Models were developed to, e.g., mine candidate selection rules from existing employee data about work behavior and retention (Chien & Chen, 2008), rank applicants based on personality traits (Faliagka et al., 2012), automatically screen resumes (Kumar et al., 2017), conduct automated psychological profiling (Tarnowski & Lapkiewicz, 2015), and predict and prevent employee churn (Dolatabadi & Keynia, 2017; Fan et al., 2012; Lin & Hsu, 2010; Sisodia et al., 2017; Yigit & Shourabizadeh, 2017). Another field emerged with regards to skill management to, e.g., assess peoples' competencies (Bohlouli et al., 2017), increase the efficiency of training schemes (Lin et al., 2011), and identify the most motivated employees (Canós-Darós, 2013). Furthermore, social network analysis gained traction to examine the formal and informal ties in organizations, which helps HR managers to, e.g., uncover collaboration and knowledge dissemination processes (De Laat & Schreurs, 2013; Hacker et al., 2017) and inform strategic initiatives, such as organizational restructuring (Gulati & Puranam, 2009; Liu & Moskvina, 2016).

## Current state (2018–2024): Advances in analytics trigger differentiation

Recently, the two research streams (predominantly managerial and predominantly technological) have begun to become more interconnected but still remain largely distinct. Given the extremely fast development of analytical methods and the abundance of computational processing capacity, the number of available people analytics approaches has skyrocketed, with some application fields advancing to individual research clusters.

Within the predominantly technological research stream, *algorithmic workforce allocation* now deals with increased complexity by running competing optimization approaches on decomposed sub-problems (Felberbauer et al., 2019;

[2] Papers that take a narrower view on people analytics typically refer to research that stems from this cluster.

Zhang et al., 2024) and applying latest methods, such as from the class of neural networks (Chen et al., 2022). Employee recruiting and turnover ("hire and fire") remain in particular focus of researchers. Within *algorithmic skill analysis*, researchers have explored a multitude of ways to support the selection of the most suitable candidates for specific job profiles based on skill and personality data captured from resumes, tests, or interviews, often applying machine learning methods to address these multi-attribute decision-making problems (Ciaschi & Barone, 2024; Maghsoodi et al., 2020; Martinez-Gil et al., 2020; Pessach et al., 2020; Xing & Wen, 2024). Another direction of research is the identification of relevant (future) skills from sources such as online job postings (Almgerbi et al., 2022; Brasse et al., 2024; Poba-Nzaou et al., 2020). Once successfully recruited and integrated, organizations aim to avoid losing employees given the potentially high replacement cost. *Algorithmic turnover prediction* is hence used to understand the flow of talent (de Vos et al., 2024a; Erden et al., 2024) and reveal the most relevant predictors of employee churn, drawing on organizational data such as employees' responses to surveys (Rombaut & Guerry, 2018) or their position in the organizational network (Ye et al., 2023). Researchers have examined differences in turnover factors across organizations (Sainju et al., 2021; Yuan et al., 2024) and cultures (Avrahami et al., 2022) as well as the effectiveness of different retention strategies (Rombaut & Guerry, 2020). A variety of machine learning algorithms have been tested in various set-ups and combinations to increase prediction accuracy for the turnover problem (Fallucchi et al., 2020; Gao et al., 2019; Srivastava & Eachempati, 2021).

As part of the predominantly managerial research stream, *analytics for performance management* has emerged as a cluster. On an overall firm level, people analytics is applied to better understand the effects of HRM practices (Becker, 2024), improve strategy execution (Levenson, 2018), and eventually contribute to higher organizational productivity, revenue, and profit (Khan et al., 2024; Schiemann et al., 2018) through HR. In conjunction with this, researchers have sought new data-supported approaches to value a company's human capital (Jin & Liu, 2021), partly in reference to the tradition of HR accounting. On the level of individual employees, new ways have been explored to understand more precisely the performance of specific staff members, increase objectivity of appraisal systems by making these more data-driven, and identify options for efficiency optimization, such as increased knowledge sharing (Nezafati et al., 2023; Nguyen et al., 2024) or improved training programs (Jain et al., 2021; Saeed et al., 2024). The respective analytics rely on data from traditional staff databases but also tap new information pools such as interaction and collaboration data (Koriat & Gelbard, 2019; Leonardi & Contractor, 2018), communication (meta-)data (Gelbard et al., 2018), and work process data from computers and other machines on-site and remote (Cinque, 2024; Kifor et al., 2021; van Hulzen et al., 2022). In many fields, recent developments in AI have led to euphoria and skepticism alike—and *artificial intelligence in HR* is no exception. Generally, AI in HR is argued to have the opportunity of augmenting or automating a wide range of (administrative) HRM tasks (Prikshat et al., 2023), personalizing HRM measures (Huang et al., 2023), and increasing cost-effectiveness (Malik et al., 2022). Organizations have started to apply respective AI tools across HRM practices, with a focus on recruitment and employee self-services (Sithambaram & Tajudeen, 2023). With regards to recruitment, AI-based approaches have been suggested to support the outreach, screening, and assessment phases of the candidate selection process (Black & van Esch, 2020). AI is now used to help HR managers judge candidates' suitability and even automate the interview process using bots (Senarathne et al., 2021; Siswanto et al., 2022). With regards to employee self-services, chatbots are increasingly used as an interface for AI tools that automate HR routine processes, such as employee onboarding, feedback collection, and answering standard questions (Majumder & Mondal, 2021; Rukadikar & Khandelwal, 2024). At the same time, a significant body of literature has developed focusing on risks and perils. Researchers address issues such as privacy (Chatterjee et al., 2022), fairness (Lavanchy et al., 2023), justice (Feldkamp et al., 2024; Newman et al., 2020), dignity (Bankins et al., 2022; Zhang & Amos, 2024), and ethicality (Yan et al., 2024). Suggested options for mitigation include transparency measures (Langer & König, 2023), the application of explainable AI (XAI) approaches (Chowdhury et al., 2023; Gao et al., 2024; Hofeditz et al., 2022), bias proofing (Vassilopoulou et al., 2024), or ethical standards (Capasso et al., 2024; Rodgers et al., 2023) and monitoring (Varma et al., 2023). More recently, the topic of generative AI has entered the discourse around people analytics, particularly regarding its strategic potential and associated risks. Emerging research highlights how generative AI can enhance HR practices—not only by automating routine tasks like writing job postings, but also by translating employee data into actionable career development strategies and aligning data insights with organizational decision-making (Aguinis et al., 2024; Korzynski et al., 2024). At the same time, concerns are raised about the potential over-dependence on generative AI as well as the potential stagnation of human creativity and critical thinking in HRM (Ardichvili et al., 2024).

Finally, researchers have investigated prerequisites, organizational implications, and success factors of *people analytics implementation*. For example, Belizón and Kieran (2022) suggest that people analytics needs to build legitimacy in an organization, for which strategic commitment, data infrastructure, and the focus of people analytics projects are relevant. Shet et al. (2021) propose a framework of success factors comprising technological, organizational, environmental, data governance, and individual aspects. Specifically with regards to the latter, researchers have evaluated, e.g., the drivers of individual willingness to adopt people analytics (Bentvelzen et al., 2024; Vargas et al., 2018) and the distinct set of competencies HR professionals need (Kulikowski, 2024; McCartney et al., 2021). Beyond that, favorable practices for implementation are suggested, such as an agile development process (McIver et al., 2018), alignment mechanisms to make sure outputs are relevant to decision-makers (Ellmer & Reichel, 2021), or the introduction of HR-specific data risk management (Calvard & Jeske, 2018).

## Results of systematic literature review: IS contributions to people analytics

In line with the research field's overall evolution, IS researchers have started to show increasing interest in people analytics over the last decade. Recently, publishing activity in the field has surged: more than half of the IS papers on people analytics that exist to date have been published in the last five years. With regards to RQ2, we find the contributions of IS scholars to be twofold. They comprise, first, the development of people analytics approaches using various analytical methods and, second, the identification of factors that enable the organizational adoption of people analytics approaches (Fig. 6).

### IS research on the development of people analytics approaches

A total of 71 out of the 122 identified articles from IS fall into this category. As illustrated in Table 1, the suggested approaches address all HRM practices and comprise different analytical methods. Similar to the findings in the bibliometric analysis, most papers propose people analytics approaches to inform HRM practices related to "hiring and firing," i.e., employee selection, allocation, and relations (which includes turnover prediction), given their high practical relevance and associated cost (Navarra, 2022; Tziner & Birati, 1996). In the following, we hence describe IS research addressing these three HRM practices in detail.

#### Approaches to inform employee selection

Employee selection is defined as the procedure of choosing the best candidate amongst multiple applicants for a specific job vacancy within an organization (Maghsoodi et al., 2020). Recently, the amount of data that is processed in employee selection has grown significantly (Qin et al., 2020). One the one hand, organizations tend to receive more applications per job offer, given the rise of remote work and hence reduced geographical constraints for many positions (Martinez-Gil et al., 2020). On the other hand, more background data is available per applicant through the proliferation of new data sources such as professional social networks (Faliagka et al., 2012). With an ever-increasing volume of data, employee selection merely through manual screening is mostly not a viable option anymore, as such processes are extremely time-consuming and prone to bias as well as decision inconsistency (Dwivedi et al., 2020). Therefore, IS researchers have proposed a range of prescriptive decision support systems which generate suggestions for HR managers on whom to potentially hire (or re-hire internally). Most commonly, these systems rely on logic-based models such as expert systems (Drigas et al., 2004; Hooper et al., 1998; Karam et al., 2020) and on machine learning-based models (Maghsoodi et al., 2020; Pessach et al., 2020; Xie, 2022; Zhu et al., 2018). They offer two main advantages to HR managers: increased efficiency through the (semi-)automation of employee selection, and increased effectiveness through the consideration of a multitude of decision factors, while the

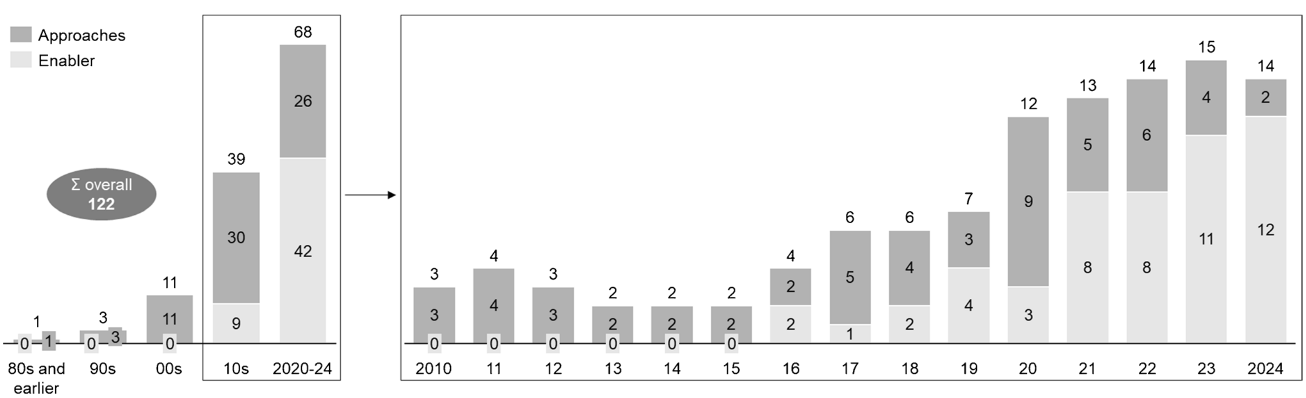


**Fig. 6** Number of IS articles on people analytics published per year

**Table 1** Overview of people analytics approaches in IS literature

\# *Number of papers using a certain approach or method (papers can refer to more than one HRM practice and analytical method)*

| HRM practice | Research focus | Data analysis approach | # | Type of analytical method | # | | # |
|---|---|---|---|---|---|---|---|
| **Analysis and design of work** 2 | *Identifying skill sets and collaboration patterns in different roles* | Descriptive | 2 | Statistical analysis | 1 | ML/data mining | 1 |
| | | Predictive | – | Logic-based models | – | Math. programming | – |
| | | Prescriptive | – | Probabilistic models | – | Evolut. computation | – |
| **HR planning** 4 | *Forecasting of human resource needs and availability (e.g., number of employees and skills)* | Descriptive | – | Statistical analysis | – | ML/data mining | 1 |
| | | Predictive | 1 | Logic-based models | 1 | Math. programming | 3 |
| | | Prescriptive | 3 | Probabilistic models | – | Evolut. computation | 1 |
| **Recruiting** 7 | *Predicting and addressing qualification gaps through hiring* | Descriptive | 1 | Statistical analysis | 1 | ML/data mining | 4 |
| | | Predictive | 4 | Logic-based models | – | Math. programming | 1 |
| | | Prescriptive | 2 | Probabilistic models | 2 | Evolut. computation | – |
| **Selection** 17 | *Screening candidates and matching them with vacancies* | Descriptive | 1 | Statistical analysis | 1 | ML/data mining | 8 |
| | | Predictive | 4 | Logic-based models | 6 | Math. programming | 3 |
| | | Prescriptive | 12 | Probabilistic models | 2 | Evolut. computation | 1 |
| **Allocation** 21 | *Optimizing job-employee matching for (project) scheduling and team formation* | Descriptive | 1 | Statistical analysis | 2 | ML/data mining | 4 |
| | | Predictive | 1 | Logic-based models | 3 | Math. programming | 9 |
| | | Prescriptive | 19 | Probabilistic models | 1 | Evolut. computation | 6 |
| **Training and development** 6 | *Forecasting skill needs and addressing them through respective training/development action* | Descriptive | 3 | Statistical analysis | 1 | ML/data mining | 2 |
| | | Predictive | 1 | Logic-based models | – | Math. programming | – |
| | | Prescriptive | 2 | Probabilistic models | 2 | Evolut. computation | 2 |
| **Compensation** 2 | *Optimizing salary levels (e.g., through benchmarking)* | Descriptive | – | Statistical analysis | 1 | ML/data mining | – |
| | | Predictive | 2 | Logic-based models | – | Math. programming | – |
| | | Prescriptive | – | Probabilistic models | 1 | Evolut. computation | – |
| **Performance management** 5 | *Predicting job performance and analyzing its determinants* | Descriptive | 3 | Statistical analysis | 1 | ML/data mining | 2 |
| | | Predictive | 1 | Logic-based models | 1 | Math. programming | – |
| | | Prescriptive | 1 | Probabilistic models | 1 | Evolut. computation | – |
| **Employee relations** 18 | *Predicting turnover and identifying drivers of employee churn risk* | Descriptive | 4 | Statistical analysis | 5 | ML/data mining | 12 |
| | | Predictive | 12 | Logic-based models | 1 | Math. programming | – |
| | | Prescriptive | 2 | Probabilistic models | 5 | Evolut. computation | 1 |

analysis often surpasses human capabilities and can potentially reduce bias (Martinez-Gil et al., 2020).

For example, Faliagka et al. (2012) present an approach to automate applicant pre-screening in online recruitment systems. Data from LinkedIn profiles, blogs, and application forms is used to infer character traits and pre-select applicants with a ranking algorithm. Chien and Chen (2008) developed a data mining framework to generate rules for personnel selection from data on characteristics and behavior (performance, retention, and turnover) of employees hired in a certain time period. The resulting "work-behavior-rules" (in the form of, e.g., "if [extent of a characteristic], then [probability of reaching a certain performance level or resigning]") can represent the basis for an organization's selection strategy. Maghsoodi et al. (2020) propose a clustering algorithm to identify the most suitable candidates across organizational functions. It is based on structured applicant data (e.g., education level, psychological scores, suggested salary) and considers a wide range of risks which could arise if the selection problem is not solved optimally (e.g., lost productivity, high absenteeism, skill shortage). Martinez-Gil et al. (2020) sought to replicate the decision-making of human experts in candidate ranking through a machine learning-based adaptive approach. Employer expectations for a role, candidate qualifications, and previous hiring decisions represent the underlying training data. In addition to identifying the most suitable candidates, Pessach et al. (2020) propose an optimization approach to maximize diversity among selected applicants. The suggested approaches are mostly evaluated with respect to predictive model performance using actual data or the judgment of human experts (Faliagka et al., 2012; Hooper et al., 1998; Martinez-Gil et al., 2020) and reporting metrics such as area under the curve (Pessach et al., 2020), mean absolute error (Malinowski et al., 2006), precision, and recall (Xie, 2022).

Despite the advances in the field, existing IS research on employee selection also entails some substantial shortcomings. First, some of the proposed decision support systems aim to merely replicate human decision-making, i.e., their target outcome is to match the decision of an expert recruiter (Hooper et al., 1998; Malinowski et al., 2006; Martinez-Gil et al., 2020). However, the underlying recruiters' logic can be inherently biased. Therefore, further research is needed to go beyond the replication of human decisions and use aspects such as expected work performance or retention as explicit target variables (Chien & Chen, 2008). Second, several suggested models are developed, trained, and tested in set-ups with significant limitations. These include a narrow focus of the underlying datasets on only few applicants' characteristics (Chien & Chen, 2008; Drigas et al., 2004; Karam et al., 2020) or limited transferability beyond a specific job type (Dwivedi et al., 2020).

### Approaches to inform employee allocation

Employee allocation refers to the decision-making process of which employee to place where (tasks, projects, roles, etc.) and when (Brusco, 2015). Conventionally, allocation models have focused on scheduling problems with the primary goal of minimizing labor costs while satisfying periodic service requirements. Numerous algorithms, including exact, heuristic, and metaheuristic approaches, have been proposed early on to automate scheduling (Yannibelli & Amandi, 2011). They are suitable for contexts with narrowly focused tasks assigned to individual employees and few complexity drivers other than HR need and availability. IS research has moved beyond this simplistic view and developed more nuanced approaches. Researchers began by considering increasingly complex time constraints for shift planning (Beaumont, 1997; Brusco & Jacobs, 1993; Brusco & Johnss, 1995). More recently, employee-specific factors such as individual skills, efficiency, or workload, are considered and the interplay of several people staffed to the same team is recognized.

For example, Farboodi et al. (2024) design a multi-objective possibilistic model for the design of virtual cellular manufacturing systems, which considers both social (e.g., cooperation interest) and technical dimensions (e.g., skills, workload balancing) of worker assignment to support flexible production planning with people analytics. Bohlouli et al. (2017) build their work upon a competence tree which encompasses professional, innovative, and social aspects. They apply a hierarchical cumulative voting approach to weigh competences and then use a clustering algorithm to identify under- and over-qualified employees. Brusco (2015) suggests a bicriterion algorithm for the allocation of cross-trained workers across multiple departments, considering both utility and (employee) desirability of a certain assignment. Shi et al. (2017) complement their skill matching approach with social network analysis and a self-organizing mechanism to minimize communication cost and find the most suitable team leaders at an optimized span of control. The algorithms proposed by Wi et al. (2009) and Liu et al. (2022) leverage social network analysis to suggest team compositions, considering skill requirements and the proximity of coworkers within an organization's social network. Researchers evaluate their approaches with regards to both, performance of underlying models—predictive performance and computational effectiveness (Bajaj & Russell, 2010; Yalçındağ et al., 2016; Yannibelli & Amandi, 2011, 2013)—and the impact on organizations. For the latter, measurements such as the utilization level and capabilities of employees (Kumar et al., 2002; Liu et al., 2022; Roy et al., 2017) are used as well as time and cost efficiency (Chen & Zhang, 2013; Shi et al., 2017; Thompson & Goodale, 2006).

Overall, IS research has helped to advance the field of employee allocation. However, many models are limited in that they only consider a given set of employee capabilities at a certain point in time and neglect the development of skills (Roy et al., 2017). Furthermore, it remains difficult to incorporate factors of human personality and relationships into models (Gutiérrez et al., 2016). Therefore, the incorporation of psychological and social aspects often remains simplistic, which affects model outcomes (Jin et al., 2020; Liu et al., 2022) and limits generalizability (Shi et al., 2017). Further limitations arise from job and industry specificity. Many research set-ups are relatively specific, with a focus on software-related project teams (André et al., 2011; Chen & Zhang, 2013).

### Approaches to inform employee relations

The costs associated with employee turnover are substantial, stemming from, e.g., the interruption of ongoing tasks and projects, reduced productivity, loss of know-how, or re-employment and re-training efforts (Chang et al., 2023; Lee & Kang, 2017). Therefore, one of the most central questions in HRM is how to prevent employees from voluntarily quitting their jobs. It is crucial for HR managers to understand the factors that influence employee churn in their organization. The measurement and management of these factors falls under the HRM practice of employee relations (Noe et al., 2017). Traditionally, survey methods were the predominant method to collect data on aspects such as employee sentiment and derive actions to retain staff. Today, survey responses remain an important source of data. This data can now be analyzed using more sophisticated approaches, such as clustering algorithms, to unveil the inclination to leave of different groups of employees based on aspects like job satisfaction, stress level, or perception of organizational politics (Fan et al., 2012). However, the use of surveys comes with certain drawbacks, such as potential social desirability bias and limited insight due to predefined questions. The advent of big data has created opportunities for more extensive and granular analyses. In turn, IS researchers have investigated ways to predict employee churn (and antecedents such as job satisfaction or absenteeism) using employee-related data that is available within organizations or from public sources.

For example, Srivastava and Eachempati (2021) and Chung et al. (2023) test different machine learning models on a combination of survey data and employee attributes documented in firm databases (e.g., salary, workload, performance, trainings) to predict churn. Deep neural networks and an ensemble model combining random forests and neural networks yield the highest accuracy. Lawrance et al. (2021) were able to show that even when relying exclusively on payroll data, employee absenteeism could be predicted, and the impact of wellbeing interventions could be evaluated. These studies illustrate the opportunity for HRM to utilize predictive models with a significantly decreased effort for manual data collection. Further potential lies in the analysis of reviews on websites such as Glassdoor, Indeed, and LinkedIn. These platforms, on which employees can rate their employer, offer a plethora of data on workplace experience. Several IS researchers have proposed the application of text mining methods (e.g., Latent Dirichlet allocation and topic modeling) to identify key predictors of job satisfaction and turnover from online reviews (Chang et al., 2023; Jung & Suh, 2019; Lee & Kang, 2017; Sainju et al., 2021). Based on the analysis of more than 1.2 million company profiles, Feng (2023) showed that the review positivity level is correlated with the financial performance of a company. Gelbard et al. (2018) demonstrate that data mining can also be used on employees' internal digital footprints (e.g., their emails) to trace emergent patterns in various human factors like employee involvement or satisfaction. The suggested approaches are mostly evaluated with respect to the predictive performance of the underlying models, using metrics such as error percentages, accuracy, recall, precision, and area under the curve for predictive models (Chang et al., 2023; Chung et al., 2023; Fan et al., 2012; Saradhi & Palshikar, 2011), and coherence or exclusivity for topic modeling (Sainju et al., 2021). Lawrance et al. (2021) went a step further and evaluated their approach using anonymized real-world HR and payroll data, which allowed them to calculate the return on investment for employee well-being interventions.

Given novel data sources, such as employees' digital footprints, people analytics in the domain of employee relations can have substantial implications for data privacy—which few papers address (Gelbard et al., 2018). Further limitations of the existing IS literature in this domain stem from the lack of generalizability. The predictive power of many suggested approaches is constrained—either by the limited number of variables included in the underlying datasets (Chung et al., 2023) or the geographical, industrial, and organizational specificity of the data used (Feng, 2023; Jung & Suh, 2019; Lee & Kang, 2017). While data from online review platforms holds significant potential for employee sentiment analysis, IS researchers also emphasize its unclear data quality (e.g., because many ex-employees write comments) and the lack of reliable demographic data of reviewers (Chang et al., 2023).

**Table 2** Overview of enablers for successful implementation of people analytics identified in IS literature

| Category | Objectives | Measures | # (Number of papers addressing a certain enabler (papers can address more than one enabler)) |
|---|---|---|---|
| **Stakeholder management** 29 | Reaching social consensus on the use of people analytics, fostering acceptance across the organization and avoiding negative reactions | Proactively considering stakeholder attitudes and tailoring communication | 23 |
| | | Educating stakeholders on function, benefits, and limitations | 12 |
| **Alignment of analytical and HR perspective** 23 | Ensuring suitability of analytical methods used, specificity of conclusions drawn, and overall consistency with organizational goals | Facilitating knowledge transfer between analytics experts and HR managers | 6 |
| | | Establishing strategic and cultural fit | 9 |
| | | Optimizing human-AI collaboration | 12 |
| **Compliance and ethics** 13 | Ensuring end-to-end data protection and privacy, promoting fairness, and limiting bias of the approaches used/conclusions drawn | Enforcing responsible data sampling and algorithm configuration processes | 8 |
| | | Proactively managing analytics-related risk (e.g., legal, ethical, and reputational) | 8 |

## IS research on enablers for the adoption of people analytics

Enablers represent the factors that help drive adoption of people analytics within organizations (Giermindl et al., 2022; Hüllmann et al., 2021). Research on enablers accounts for 51 out of 122 identified IS articles (each paper can address more than one enabler category, see Table 2) and can be divided into three categories: stakeholder management, alignment of analytical and organizational perspective, and compliance and ethics. For each of these categories, existing IS research provides concrete enabling measures.

### Stakeholder management

Research in this category focuses on identifying, prioritizing, and engaging with different stakeholders—as they often have differing perspectives and concerns regarding the adoption and use of people analytics—to enable the implementation (Hülter et al., 2024; Kinowska & Sienkiewicz, 2023; Laurim et al., 2021; Malin et al., 2024; Ochmann, 2020; Pillai et al., 2024). While people analytics can, e.g., enhance decision-making fairness and improve job satisfaction (Angrave et al., 2016; Kinowska & Sienkiewicz, 2023; Tursunbayeva et al., 2019), its implementation can also have unintended negative effects, such as eroding stakeholders' trust, reducing job autonomy, and diminishing perceptions of justice (Bankins et al., 2022). Primary stakeholders, including employees, managers, and HR professionals, are impacted most by these effects and should hence play a key role in shaping people analytics implementation. Secondary stakeholders, such as civil society, regulators, and the press, play an indirect role as they contribute to the broader discourse and can influence the acceptance of people analytics (Fassin, 2012). Given the various interests and concerns of the different groups, it becomes essential to navigate the complexities of stakeholder management—the goal of which should be to achieve social consensus on people analytics use within and beyond organizations (Kim & Heo, 2022; Klöpper & Köhne, 2022). To this end, IS researchers propose two types of measures.

**Proactively considering stakeholder attitudes and tailoring communication** This measure, widely emphasized in IS literature, involves understanding the attitudes of stakeholders affected by people analytics and addressing these attitudes in tailored communication. The latter hence becomes a proactive tool to foster social consensus. This emphasis is supported by empirical evidence: a study by Kinowska and Sienkiewicz (2023), involving over 20,000 European organizations, confirms the importance of consistently monitoring and analyzing employees' attitudes and opinions on the use of autonomous, data-driven decision-making in HRM. A regular analysis of these attitudes helps mitigate negative reactions to management decisions based on people analytics. Furthermore, Suen et al. (2019) demonstrate the importance of identifying conditions under which negative attitudes arise. Specifically, they show that fairness concerns can emerge when decision-making processes appear impersonal or lack transparency. Clear and proactive communication can mitigate such concerns by providing information about how decisions are made and how data is used. Similarly, van den Broek et al. (2019), through an ethnographic study on the use of AI in hiring at a multinational company, find that stakeholder attitudes evolve over time during the development and use of people analytics in practice. Their findings underscore the need for continuous communication efforts to address shifting attitudes, align expectations, and ensure that differing perspectives are acknowledged and reconciled as technology evolves. Building on this line of evidence, Ongena et al. (2024) highlight the practical importance of transparent communication in stakeholder management. Drawing on survey data from 127 HR professionals in public agencies, they show that clearly communicating the anticipated benefits of people analytics initiatives can help mitigate concerns about associated costs and enhance perceived value. Their findings underscore that communication is not merely a supportive practice, but a key mechanism for shaping employee perceptions and expectations—and ultimately for supporting the adoption of people analytics within organizations.

**Educating stakeholders on function, benefits, and limitations** IS researchers further emphasize the need for organizations to adopt an educative role, focusing on enhancing stakeholders' understanding of the benefits and limitations of people analytics. Educated employees have been shown to have a more substantiated attitude toward people analytics and perceive workplace treatment to be more respectful. Training programs should be designed that take into account stakeholders' varying levels of trust in people analytics, as well as differences in age and cultural backgrounds (Bankins et al., 2022). Moreover, education can be facilitated by adopting "low-threshold methods," such as transparent design approaches, which empower users to assess the potential of people analytics and foster trust in its applications (Klöpper & Köhne, 2022). Improving interpretability is considered particularly important, as people analytics approaches often operate as opaque "black boxes." For instance, Hofeditz et al. (2022) show in an online experiment involving 194 participants that XAI approaches allow HR managers to augment their decision making, reflect on their (potential) biases, and better understand the reasons for AI-based system recommendations. Tian et al. (2023) demonstrate that process explanations (e.g., how the system works, what data is used) and outcome explanations (e.g., why a specific decision was made) help users mentally reconstruct the logic behind algorithmic outcomes, leading to greater transparency, increased perceptions of fairness, and more informed engagement with AI-based systems.

Overall, within the category *stakeholder management*, research highlights the critical importance of considering stakeholder attitudes through tailored communication strategies and targeted educational initiatives. However, a gap in the current IS literature remains in understanding which specific aspects of people analytics approaches induce stakeholder concerns and at what stages of implementation these concerns are most likely to arise. This lack of clarity makes it difficult to identify precisely where and when targeted interventions are needed. Additionally, much of the existing IS literature on this topic has limited generalizability due to its reliance on specific participant samples (Tomprou & Lee, 2022), the use of hypothetical scenarios (Baum et al., 2023; Ochmann, 2020), and a narrow focus on selected technologies (Black & van Esch, 2020).

### Alignment of analytical and organizational perspective

Research in this category focuses on aligning analytical and organizational perspectives to effectively manage the implications of people analytics approaches. In the evolving landscape of people analytics, organizations face the dual challenge of leveraging advanced analytical capabilities while ensuring alignment with HR practices and broader organizational objectives (Angrave et al., 2016). IS research mainly suggests three measures to address these challenges: bridging expertise gaps between analytical experts and HR managers, aligning people analytics with strategic and cultural goals, and optimizing human-AI collaboration. These measures aim to unlock the full potential of people analytics, enhancing both its adoption and its strategic value.

**Introducing knowledge transfer processes between analytical experts and HR managers** The success of people analytics relies on collaboration between analytical experts and HR managers, yet these two groups often operate in silos, limiting potential impact (Marler & Boudreau, 2017). Analytical experts, while skilled in data interpretation and complex modeling, frequently struggle to contextualize their findings within the nuances of HRM practices (Someh et al., 2023). Conversely, HR managers often lack the technical expertise needed to leverage advanced analytical tools and methodologies effectively, creating a gap that hinders the integration of data-driven insights into strategic decision-making processes (Angrave et al., 2016). To bridge this gap, van den Broek et al. (2021) suggest that analytical experts and HR managers should establish an interdependent relationship: HR managers play a vital role in defining, evaluating, and refining people analytics approaches, while analytical experts uncover novel insights to enhance HR practices. Building on this, other IS researchers propose solutions that address the collaborative dynamics of this relationship through team formation. Stelmaszak (2022) emphasizes that embedding data science teams within people analytics units supporting HR functions can maximize strategic value. These teams are most effective when integrated into strategic decision-making while retaining autonomy over specific tasks, enabling both alignment with organizational goals and the flexibility to innovate. Similarly, Someh et al. (2023) stress that dedicated data teams and multidisciplinary groups—comprising members from both analytics and HR functions—promote innovative, data-driven HR practices. Furthermore, embedding analytics into routine workflows and ensuring analytics tools are accessible organization-wide further enhances the adoption of people analytics, standardizing data-driven methods and encouraging their broad application.

**Establishing strategic and cultural fit** Strategic fit ensures alignment between people analytics and organizational goals (Zajac et al., 2000). IS researchers emphasize the critical importance of establishing strategic fit. For example, Werkhoven (2017) suggests that a reciprocal relationship between organizational and HR strategies, where people analytics forms and shapes both while drawing guidance from them, can create a reinforcing cycle that enhances the impact of analytics on decision-making and strategic execution. However, without cultural fit, i.e., addressing the behavioral and normative aspects essential for its adoption and effective use (Mendonca & Kanungo, 1994), even strategically aligned analytics initiatives may face resistance or fail to integrate effectively into the organization's daily operations. This view is supported by recent empirical work from Ongena et al. (2024), who find that the perceived value of people analytics increases when such systems are not only technically compatible with existing infrastructures but also embedded in a cultural context that is open to innovation and change. Initial innovative studies provide approaches for achieving cultural fit. For example, Gierlich-Joas and Zimmer (2023, p. 11) find that transforming the identity of HRM is essential. They propose that a shift from a traditional "value proposition of reporting" to one of "employee empowerment" fosters an environment where people analytics can thrive, enabling employees to leverage insights for personal and organizational growth while promoting trust, collaboration, and shared purpose.

**Optimizing human-AI collaboration** Given the sensitivity of decisions and data in people analytics, relying on AI poses significant challenges (see also the cluster *artificial intelligence in HR* in the bibliometric analysis). Regulations such as the EU AI Act reinforce the need for human oversight in AI-driven decision-making processes. IS researchers therefore stress the importance of optimizing human-AI collaboration in people analytics: organizations should curb unquestioned datafication—where employees are reduced to mere collections of digital data generated by their daily activities—by encouraging human interpretation in decision-making and using multiple information formats and sources, including non-data-based insights. Otherwise, organizations risk perpetuating a cycle of opacity, reductionism and manipulation that can undermine employees' ability to develop practical knowledge and thrive in their roles (Gal et al., 2020). IS research further supports the role of AI as a collaborative partner: Cheng et al. (2021) highlight that while AI excels at processing data and identifying patterns in people analytics, its integration with human expertise is essential for addressing complex, context-dependent aspects of strategic decision-making. Similarly, Bankins et al. (2022) emphasize the importance of preserving a meaningful human role in decision-making, whether by monitoring AI outputs (on-the-loop) or actively collaborating with AI systems (in-the-loop), though they refrain from outlining specific implementation strategies. This view aligns closely with the FAT-CAT model by Lee and Cha (2023, p. 10), which frames "human-AI augmentation, in which humans make the final decision," as a prerequisite for effective and equitable people analytics adoption.

Overall, within the category *alignment of analytical and organizational perspective*, the findings acknowledge the importance of ensuring suitability of analytical methods, specificity of conclusions, and alignment with organizational goals. While research recognizes the significance of establishing strategic and cultural fit and optimizing human-AI collaboration, it falls short in offering concrete implementation strategies. Moreover, there is a notable lack of empirical evidence supporting these measures, leaving the impact of such alignment largely unexplored.

### Compliance and ethics

Research in this category proposes mitigation measures to proactively manage ethical and compliance risks so that people analytics is not only effective but also responsible and fair. Although people analytics is promising for enabling more objective and accurate decision-making, it also introduces significant ethical risks, such as privacy violations (Drake et al., 2016), algorithmic bias (Köchling et al., 2021; Zheng et al., 2024), and lack of transparency (Hofeditz et al., 2022). This research stream builds on broader discussions of compliance and ethics in people analytics beyond the IS domain (see results of bibliometric analysis) while highlighting concrete measures during and beyond people analytics system development.

**Enforcing responsible data sampling and algorithm configuration processes** Bias in people analytics arises when algorithms, inherently data-driven, learn and perpetuate biases from training data or exhibit bias due to configuration processes—a particularly critical issue when dealing with sensitive, people-related data (Klöpper & Köhne, 2022; Mehrabi et al., 2021). For example, Köchling et al. (2021) illustrate how underrepresentation of certain genders and ethnicities in training datasets can lead to discriminatory outcomes, such as biased interview invitations based on an analysis of 10,000 recruitment video clips. These biases not only distort results but also deepen systemic inequalities. To mitigate these risks, researchers emphasize proactive measures, with a focus on curating representative and inclusive training datasets, conducting regular algorithm audits (with configuration and performance reviews), and implementing robust governance structures that combine algorithmic and human oversight (Kim & Heo, 2022; Köchling et al., 2021).

**Proactively managing analytics-related risks (e.g., legal, ethical, and reputational)** Beyond challenges such as data bias and algorithmic configuration issues, people analytics introduces a broader spectrum of risks encompassing legal, ethical, and reputational dimensions. These risks extend into social and organizational domains, such as the potential misuse of employee data to monitor performance excessively or unfairly influence promotion decisions (Calvard & Jeske, 2018; Fumagalli et al., 2022; Klöpper & Köhne, 2023). Several IS researchers examine the downsides and unintended consequences of people analytics and propose strategies for managing them effectively. Klöpper (2023), e.g., develops a conceptual model on employees' perception of people analytics usage in an organization and finds that people analytics can raise privacy concerns and erode employee trust, potentially leading to turnover. Klöpper and Messer (2024) show that the perceived involvement of people analytics in personnel decisions can trigger feelings of betrayal and moral violation. These emotional responses, in turn, increase demands for accountability and can lead to retaliatory behavior towards managers and the organization. To mitigate these risks, Calvard and Jeske (2018) advocate for comprehensive risk management frameworks that balance people analytics' potential with safeguards for fairness, transparency, and employee rights. The researchers emphasize responsible data governance, transparent practices, cross-departmental collaboration, and proactive measures such as system-wide audits to maintain trust and protect employee privacy. Zhang et al. (2020) propose fairness rules, including the "ethicality rule," which emphasizes minimizing manipulation and protecting privacy, offering practical guidance to design people analytics approaches responsibly.

Overall, within the category *compliance and ethics*, IS researchers increasingly propose measures to tackle respective risks in people analytics. However, much of this work remains theoretical, with limited empirical research to support these discussions (Klöpper & Köhne, 2023).

## Discussion

As we established at the beginning of this paper, people analytics has not yet fully unleashed its alleged potential to create business value from data. Several shortcomings in the field hinder the further development of people analytics in theory and practice. Given the IS discipline's dual lens at the interface of technology and management, it is particularly suited to advance the field of people analytics and help overcome existing research gaps (Hevner & March, 2003). By establishing intertextual coherence of existing knowledge (Locke & Golden-Biddle, 1997), this paper aims to create impulses for IS research to deliver on its integrative promise. This section is dedicated to generating such impulses. Following the "theory-generating avenue" of "exposing emerging perspectives" (Post et al., 2020, p. 355), we synthesize the findings from our literature review into an integrative framework of people analytics with a focus on business value creation and deduce a research agenda.

### Towards an integrative framework of business value creation through people analytics

Our review confirms earlier findings from the IS discipline (Werkhoven, 2017) and the HR discipline (Marler & Boudreau, 2017) that no coherent, empirically grounded understanding exists of how people analytics can create business value. Hence, the common critique that people analytics mostly lacks a clear link to specific business problems and organizational outcomes (Ben-Gal, 2019; Larsson & Edwards, 2022; Rasmussen & Ulrich, 2015) remains up-to-date. The few theoretical models that exist to date include conceptualizations from HRM research of the success factors (Douthitt & Mondore, 2014) and key components for HR measurement systems to drive "strategic change and organizational effectiveness" (LAMP framework) (Boudreau & Ramstad, 2007, p. 191). A small number of researchers from the IS discipline have begun to contribute to this research stream. Werkhoven (2017) discusses the organizational capabilities necessary for value creation through people analytics, drawing on a process model from business analytics. McCartney and Fu (2022a) establish that people analytics positively impacts organizational performance, with the relationship being mediated by an organization's capacity for evidence-based management. Stelmaszak (2022) suggests that data scientists involved in people analytics engage in data crafting, an approach to ensure that their analyses hold strategic value for their organization. Overall, theoretical perspectives on people analytics and value creation remain scarce.

Therefore, in this first part of our discussion, we synthesize the findings from our literature review to derive a novel integrative framework of business value creation through people analytics. It extends existing theory—by taking a more holistic perspective and integrating the technological with the managerial perspective on people analytics—and shall serve as a basis for further IS research. In IS research, such integrative approaches are commonly used to consolidate accumulated knowledge on a topic identified through a literature review by abstracting and integrating underlying concepts and, as a result, developing a sound basis for future research (Cram et al., 2016; Melville et al., 2004; Pool et al., 2024; Saunders, 1981). We base our framework on the resource-based view of the firm (RBV), as suggested, e.g., by McCartney and Fu (2022b). The RBV fundamentally establishes that it is through their unique sets of internal resources that firms attain competitive advantage (Penrose, 1959; Wernerfelt, 1984). More specifically, it implies the duality of resource possession and use, i.e., that resources have to be used in certain ways to create value (Barney, 1991). The latter has been commonly interpreted as a context-specific, appropriate alignment of resources (D'Oria et al., 2021). With regards to resource possession, the definition of people analytics already implies that value is created by leveraging three resources that are uniquely pronounced in each organization: HRM, data/technology, and employees. While this notion of which resources are involved in people analytics is well-established, as discussed above, it is not equally clear how these components are to be configured best to create business value. To identify dimensions of resource use, we adopt the process for configurational theorizing proposed by Furnari et al. (2021). Configurational theorizing of a phenomenon is based on attributes (explanatory factors) and configurations (constellations of attributes connected by orchestrating themes). Furnari et al., (2021, p. 784) propose a three-stage theorizing process that involves scoping ("identifying relevant attributes"), linking ("specifying how the attributes connect [...] in specific configurations"), and naming ("labeling configurations to evoke their orchestrating themes"). For this study, in which we treat existing literature as data, the findings from our systematic literature review represent the relevant attributes (scoping stage)— i.e., the nine research foci we identified with regards to people analytics approaches (see Table 1) and the seven measures we identified with regards to people analytics enablers (see

**Table 3** Results from configurational theorizing (* Apr. = people analytics approach, Enb. = enabler)

| Configurations | Orchestrating themes | Attributes (findings from systematic literature review) | Apr.* | Enb.* |
|---|---|---|---|---|
| **Strategy** | Rather long-term, strategic perspective | Establishing strategic and cultural fit | | • |
| | | Proactively managing analytics-related risk | | • |
| | | Enforcing responsible data sampling and algorithm configuration processes | | • |
| | | Forecasting human resource needs and availability | • | |
| | | Predicting and addressing qualification gaps through hiring | • | |
| | | Predicting turnover and identifying drivers of employee churn risk | • | |
| | | Identifying skill sets and collaboration patterns in different roles | • | |
| | | Optimizing salary levels | • | |
| **Operations** | Rather short-term, tactical perspective | Proactively considering stakeholder attitudes and tailoring communication | | • |
| | | Screening candidates and matching them with vacancies | • | |
| | | Optimizing job-employee matching for (project) scheduling and team formation | • | |
| | | Predicting job performance and analyzing its determinants | • | |
| **Knowledge and skills** | Underlying capability perspective | Educating stakeholders on function, benefits, and limitations | | • |
| | | Facilitating knowledge transfer between analytics experts and HR managers | | • |
| | | Optimizing human-AI collaboration | | • |
| | | Forecasting skill needs and addressing them through respective training/development action | • | |

Table 2). To identify the attributes' underlying orchestrating themes and combine the attributes into configurations (linking stage), we follow the heuristics suggested by Furnari et al. (2021), namely thinking conjunctively, thinking equifinally, and thinking about absence. Finally, we label the configurations (naming stage) to capture their essence (see Table 3).

Synthesizing the findings from our systematic literature review yields three configurations. First, the *strategy* configuration entails those findings with a primarily strategic perspective, i.e., people analytics procedures and enablers that have a rather long-term orientation and higher-level scope. Second, the *operations* configuration entails those findings with a primarily tactical perspective, i.e., people analytics procedures and enablers that have a rather short-term orientation and task-specific scope. Third, the *knowledge and skills* configuration entails those findings that are primarily capability-focused, i.e., people analytics procedures and enablers that ensure the provision of the necessary underlying understanding, know-how, and capacity of involved actors. Next, we integrate these findings regarding resource possession and resource use into a novel framework of business value creation through people analytics. Based on the RBV, our integrative framework proposes that, while each resource in itself should be developed (optimized), they cannot exist largely monolithically next to each other, if people analytics is to substantially contribute to business value. Instead, all resources in their entirety need to be aligned across the three identified dimensions of strategy, operations, and knowledge and skills. Concretely, this implies that any people analytics action, no matter which of the three resources is initially in focus, always impacts the other two—on at least one dimension and in a way that can either create or destroy business value. Graphically, these relationships of coaction and interdependence are illustrated by the arrows and permeable boxes in Fig. 7.

While our integrative framework advances the theoretical understanding of how people analytics can create business value in particular, it also contributes to the broader research streams on value creation through HRM and IT in general. In the literature on strategic HRM, the link of HRM to organizational performance has been discussed widely (Lengnick-Hall et al., 2009) but partly still remains a "black box" (Jiang et al., 2013, p. 1448). It has however been established that value creation through HRM can be enhanced by building and integrating HRM practices and human capital (Apascaritei & Elvira, 2022; Huselid, 1995; Liu et al., 2007). In the literature on electronic HRM, IT has been demonstrated to function as an enabler of value creation through HRM by facilitating practice-specific efficiency gains (e.g., effort reduction in application screening) and supporting new, more strategic HRM roles (e.g., as a

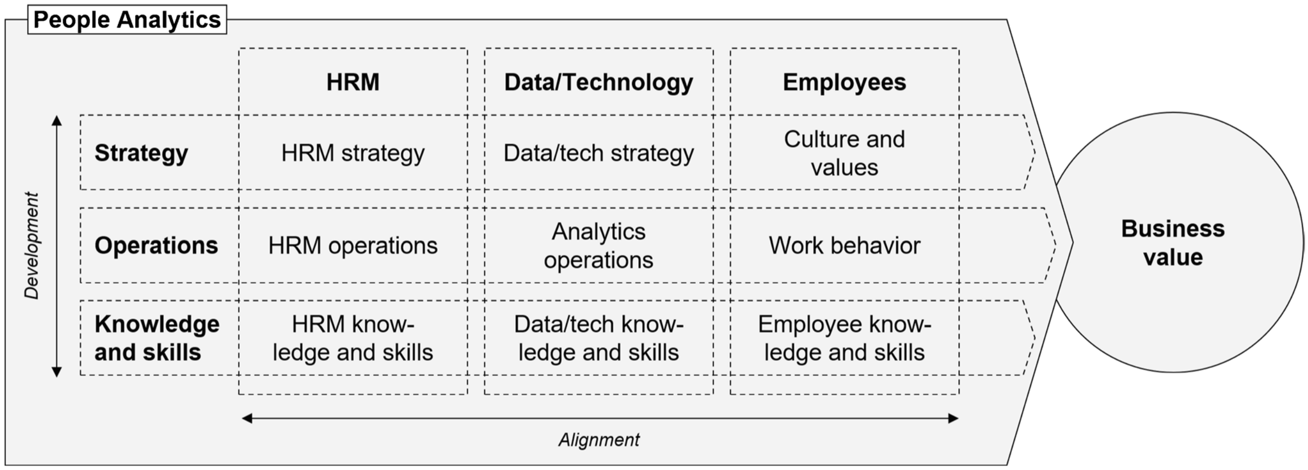


**Fig. 7** Integrative framework of business value creation through people analytics

business partner and change agent) (Bussler & Davis, 2002; Haines & Lafleur, 2008; Zhang & Chen, 2024). More specifically, it has been established that HRM, IT, and human capital are to be enhanced individually and integrated as a whole to drive business value (Oehlhorn et al., 2020; Wirtky et al., 2016; Zhou et al., 2022). Against this background, our research confirms and extends existing theory on value creation through HRM and IT by conceptualizing value creation as the joint holistic development and alignment of the triad of HRM, data/technology (IT), and employees (human capital) across the dimensions strategy, operations, and knowledge and skills (for the context of people analytics). In the following, we use our integrative framework to structure our people analytics research agenda.

## A people analytics research agenda for the IS discipline

In this second part of our discussion, we describe concrete research opportunities across the three key resources involved in people analytics—HRM, data/technology, and employees. Concretely, we suggest that future IS research address each resource across the three dimensions strategy, operations, and knowledge and skills (development) as well as the synergies and tensions between them (alignment). Therefore, both aspects are reflected in the research opportunities and potential research questions we present below.

### Development of HRM as a resource in people analytics (Table 4)

**Increase the focus on the strategic dimension of HRM** Macro trends such as workplace digitalization, the shift to knowledge work, and vanishing employee loyalty have led to an even stronger emphasis on the strategic role of HR as a business partner with people analytics as an important catalyst (Cassar et al., 2023; Ulrich et al., 2017). On the one hand, people analytics can enable HR managers to act (more) strategically (Hamilton & Sodeman, 2020; Pessach et al., 2020). On the other hand, people analytics needs strategic commitment and guidance as a basis for legitimacy and relevance in an organization (Belizón & Kieran, 2022). So far, the IS discipline largely fails to reflect this strategic dimension. The majority of works take a rather operational perspective in that they aim to optimize and automate specific HRM tasks. An opportunity for IS researchers lies in expanding this perspective by investigating how HRM strategy can be embedded in people analytics—and how people analytics can help shape strategy. Some research papers take a step into this direction by focusing on strategic aspects such as benefits and incentives for staff retention (Srivastava & Eachempati, 2021), cost-effective intervention campaigns for absenteeism (Lawrance et al., 2021), or the impact of people analytics on HRM's role, identity, and behavior (Gierlich-Joas & Zimmer, 2023; Stelmaszak, 2022).

**Apply a holistic perspective across HRM practices and processes** More than two-thirds of the people analytics approaches proposed in IS research focus on "hire and fire," i.e., employee selection, allocation, and churn prevention, which represent the most obvious practices in HRM. While some studies address challenges such as employee satisfaction (Goldberg & Zaman, 2018), knowledge sharing (Koriat & Gelbard, 2019), and strategic workforce planning (Berk et al., 2019), IS researchers have not yet sufficiently considered the wide range of HRM practices. Particularly, more research is needed on people analytics approaches for analysis and design of work, compensation, performance

**Table 4** Overview of research opportunities—development of HRM as a resource in people analytics

| Research opportunities | Inspirational examples | Potential research questions |
|---|---|---|
| **HRM strategy:** Increase the focus on the strategic dimension of HRM | Gierlich-Joas and Zimmer (2023), Stelmaszak (2022), Lawrance et al. (2021) | How can a holistic, strategic HRM perspective be ensured in people analytics systems that goes beyond insights for specific HRM practices?<br>How can dynamic people analytics systems be designed that reflect changing goals/targets and at the same time help shape HR strategies?<br>Through which mechanisms do people analytics systems impact the role of HRM as strategic business partner in organizations? |
| **HRM operations:** Apply a holistic perspective across HRM practices and processes | de Vos et al. (2024b), Ongena et al. (2024), Ekka and Singh (2022) | How can people analytics systems be designed for yet under-researched practices such as training, design of work, or compensation?<br>How can holistic people analytics systems be designed that incorporate the entirety of HRM practices?<br>How can technology acceptance models be adapted/developed for people analytics usage and its integration to HRM standard processes? |
| **HRM knowledge and skills:** Expand the user perspective in people analytics systems design | Dwivedi et al. (2020), Karam et al. (2020), Bohlouli et al. (2017) | How can human experience and expertise in HRM be inherently incorporated in people analytics systems?<br>How can people analytics systems be designed that help increase human-machine complementarity in HRM decision-making?<br>How can existing approaches of design science research be utilized to advance user orientation in people analytics systems design? |

management, and training and development—such as the work by de Vos et al. (2024b) on data-driven internal employee mobility. Works from other disciplines identified in our bibliometric analysis illustrate further possible directions, such as people analytics for up- and reskilling (Agarwal et al., 2022), identification of possible career paths (Zhu et al., 2023), or management of employees' mental well-being (Lathabhavan, 2024). Taking a broader perspective beyond single HRM practices, it would be worth gaining deeper insight into how the application of people analytics (potentially) changes the existing standard processes of HRM and how it could be incorporated into the everyday toolkit of HR managers. This requires adoption readiness and technology acceptance, which is profoundly theorized in IS with models such as the technology organization environment framework (TOE), the technology acceptance model (TAM), or the unified theory of acceptance and use of technology (UTAUT). However, research papers applying and developing such theory in the context of people analytics (Ekka & Singh, 2022; Ioakeimidou et al., 2024; Lee & Cha, 2023; Ongena et al., 2024) are still rare. Further research is needed to substantiate the understanding of people analytics acceptance and adoption.

**Expand the user perspective in people analytics systems design** People analytics systems that are designed to make fully automated decisions about employees are likely to raise ethical and legal concerns (e.g., under the EU's General Data Protection Regulation). Moreover, various IS studies have shown that better decision-making results can be achieved through complementarity of machine and human judgment (Fügener et al., 2021; Hemmer et al., 2021). HR managers should hence be involved in not only the evaluation of people analytics output, but also the conceptualization and design of respective systems. However, existing IS research hardly incorporates HR managers' expertise and needs. Therefore, we suggest that, on the one hand, future academic works address questions of human–computer interaction and complementarity—a key concern of the IS discipline overall—in the context of people analytics. On the other hand, the field would profit from more design science research—one of the key research paradigms in IS (Hevner et al., 2004)—with a strong focus on HR managers as users (Bajaj & Russell, 2010). Initial promising examples include studies which have involved users for the identification and adjustment of model factors and weights (Bohlouli et al., 2017; Dwivedi et al., 2020; Karam et al., 2020).

### Development of data/technology as a resource in people analytics (Table 5)

**Leverage the potential of rich data sources better** In line with the finding that people analytics is not yet applied across the entirety of HRM practices, the types of data utilized also have a relatively narrow focus. About 60% of the IS papers proposing people analytics approaches rely on only one or very few of the five most common data types, which are general employee attributes (such as age, gender, role, etc.), skill data, performance data, task specifications, and application data. Other data types are utilized in less than 10% of papers. Moreover, existing works are often limited in their time and feature coverage—e.g., they lack historical data (Roy et al., 2021) or consider only a limited number of employee characteristics (Karam et al., 2020). As a result, the range of insights to be generated is limited, changes over time cannot be accounted for, and the risk of bias may be increased. It is therefore imperative for IS researchers to take a wider perspective on current data sources (e.g., through longitudinal studies) and to explore entirely new sources. While it is crucial to carefully consider ethical and legal boundaries, such new sources might include data from communication and collaboration tools (Koriat & Gelbard, 2019) or even sensor data from wearables to capture, e.g., physical movement of production workers (Tran et al., 2023) or cognitive functions of executives (Zazon et al., 2023). Another opportunity is to explore the management of data quality in the context of people analytics, which can help increase analytics output quality while decreasing bias and fairness risks. A wide range of research on data quality exists in the IS discipline (Sadiq et al., 2011), but its methods are yet to be adapted and further developed for the field of people analytics. Lastly, particularly when widening the range of data sources in scope, it is important to ensure efficient data management (Pape, 2016) as well as congruence and consistency across systems (Zhou & Zou, 2023). To this end, IS researchers should explore the integration and reflection of people analytics in the wider IT and data strategy of an organization.

**Advance a full-range utilization of analytical methods** To date, IS research has generally suggested a broad range of analytical methods for people analytics. However, their application levels vary greatly. For example, while several optimization approaches have been introduced to solve allocation problems, they have been neglected for other, equally relevant questions (e.g., workplace features to improve employee well-being, salary levels to increase employee engagement, or feedback mechanisms to increase employee performance). Another method that holds significant potential for people analytics is social network analysis. Papers from adjacent research fields identified in our bibliometric

**Table 5** Overview of research opportunities—development of data/technology as a resource in people analytics

| Research opportunities | Inspirational examples | Potential research questions |
|---|---|---|
| **Data/tech strategy:** Leverage the potential of rich data sources better | Zazon et al. (2023), Tran et al. (2023), Pape (2016) | Which untapped types of data are most valuable for people insights to be generated (e.g., collaboration data) and how can they be combined?<br>Which data quality metrics and actions are most suitable to mitigate issues of bias and fairness in a critical field such as people analytics?<br>In which ways should people analytics be integrated to organizations' data and technology strategy to ensure its efficiency and effectiveness? |
| **Analytics operations:** Advance a full-range utilization of analytical methods | Semujanga and Mikalef (2024), Hofeditz et al. (2022), Boeva et al. (2018) | How can generative AI be incorporated to people analytics systems and what value does it hold in this context?<br>How can XAI methods be adapted and developed to increase the interpretability of people analytics approaches?<br>How can approaches of social network analysis be developed to generate deeper insights in HRM practices such as employee relations? |
| **Data/tech knowledge and skills:** Strengthen a human-focused evaluation beyond the technological perspective | Gierlich-Joas et al. (2024), Hülter et al. (2024), Tian et al. (2023) | What is an appropriate balance of technology- and human-centered evaluation in people analytics given its specific characteristics?<br>Which dimensions are most relevant in applying a human-centered evaluation approach to people analytics?<br>Which existing IS evaluation approaches and frameworks are most suitable to be applied in the context of people analytics? |

analysis provide evidence that this method can support complex HRM tasks such as identifying (hidden) knowledge (Caron & Batistic, 2019) or unveiling informal connections between employees in comparison to formal connections as a basis for evaluation and improvement of organizational structures (Boeva et al., 2018; Gulati & Puranam, 2009). However, few IS researchers have touched upon this huge potential so far. Future works should draw upon the extensive knowledge on social network analysis in the IS discipline and develop it further for the context of people analytics. Besides, researchers have recently started to investigate the potential of generative AI for HRM (Budhwar et al., 2023; Parker et al., 2023; Semujanga & Mikalef, 2024). Amid the rapid evolution of large language models and the early stage of related research, IS researchers with their combined technological and managerial perspective are well-positioned to provide orientation and help shape what could represent a leap innovation for people analytics. Despite the enthusiasm, a growing number of people analytics approaches will—or already do—lack explainability (Chang et al., 2023; Chung et al., 2023; Xie, 2022). Such black-box models are particularly problematic in a field where technology supports decisions about (individual) human beings and may negatively impact trust and acceptance of people analytics systems. It is therefore surprising that only very few authors include explanatory approaches from the field of XAI in their works (Chowdhury et al., 2023; Gao et al., 2024; Hofeditz et al., 2022). IS researchers should draw upon the considerable body of XAI knowledge in the discipline (Brasse et al., 2023) to help mitigate the opaque character of many models.

**Strengthen a human-focused evaluation beyond the technological perspective** Existing IS research in people analytics leaves room for the exploration of a wider range of evaluation methods. While some researchers test people analytics approaches in case study settings (Farboodi et al., 2024; Hülter et al., 2024) or validate their findings with human experts (Faliagka et al., 2012; Malin et al., 2024), many works tend to take a technology-oriented rather than a human-oriented evaluation perspective. In their evaluations, authors focus on predictive performance metrics (Carpenter et al., 2018; Xie, 2022) or algorithmic efficiency metrics such as computation time (Yannibelli & Amandi, 2013). Human-oriented evaluation dimensions, such as usability, transparency, trust, or perceived justice and fairness, are rarely used and few authors conduct user studies to test these dimensions (André et al., 2011; Gierlich-Joas et al., 2024; Tian et al., 2023)—even though a wide range of human-oriented and integrated evaluation methods and frameworks, such as FEDS (Venable et al., 2016), is in fact available in the IS discipline. In this regard, IS researchers are well-positioned to overcome the often one-dimensional, "purely technical" (Venable et al., 2016, p. 80) approaches. Expanding the work on human-oriented evaluation should go hand in hand with deepening the user focus in people analytics systems design.

**Table 6** Overview of research opportunities—development of employees as a resource in people analytics

| Research opportunities | Inspirational examples | Potential research questions |
|---|---|---|
| **Culture and values:** Evaluate the influence of organizational culture | Arena et al. (2023), Gurusinghe et al. (2021), Sherif et al. (2021) | Which aspects of organizational culture are most relevant for the success of people analytics in the long run?<br>How can a positive feedback loop between organizational culture and people analytics be conceptualized and achieved?<br>Which IS models on the impact of organizational culture on information systems should be developed further for the context of people analytics? |
| **Employee behavior:** Blend people analytics and work process perspective | Farboodi et al. (2024), Liu et al. (2022), Strohmeier and Röhrs (2017) | What conceptual frameworks can effectively link people analytics with process analytics to optimize human and operational efficiency factors?<br>Which additional insights can be generated in people analytics if performed in concurrence with work process analytics?<br>How can people analytics be integrated into everyday work processes to inform employees as well as HR and line managers? |
| **Employee knowledge and skills:** Explore the positive potential for employees as active users | Di Prima et al. (2024), Zieglmeier and Pretschner (2023), Gal et al. (2020) | How can people analytics approaches be designed to provide agency and oversight to employees as active users?<br>How can people analytics approaches be designed to support growth and well-being of employees as active users?<br>What (measurable) benefits emerge when employees are positioned as active users rather than passive objects of analysis? |

### Development of employees as a resource in people analytics (Table 6)

**Evaluate the influence of organizational culture** A wide range of IS literature has shown that organizational (or corporate) culture has an impact on the development, use, and outcomes of IS in general (Leidner & Kayworth, 2006). Some early research proposes that a data-driven culture that promotes decision-making based on insights generated from data influences people analytics capabilities and outcomes in particular (Gurusinghe et al., 2021). Yet very few works deliver empirical evidence (Sherif et al., 2021). Conversely, people analytics can help shape and cultivate organizational culture, e.g., by examining the diffusion of culture attributes throughout an organizational network (Arena et al., 2023). So far, papers in key IS outlets address the relevance of corporate culture for people analytics only indirectly through aspects such as stakeholder management, compliance, and ethics (see section on people analytics enablers). IS researchers are hence encouraged to explore the impact of organizational culture on people analytics and respective value creation by expanding existing theory on culture and IS as well as developing new theory and approaches for the context of people analytics. For example, researchers might want to explore the potential for the creation of a feedback loop in which people analytics strengthens culture and a strong culture, in turn, enhances the impact of people analytics.

**Blend people analytics and work process perspective** As soon as people have joined a firm after a successful recruitment process, much of the data used in people analytics is collected during employees' everyday work, hence depicting their work behavior. Given that for many professions, a majority of workflows are (or at least can be) described in (more or less standardized) work processes, a natural overlap exists. It follows logically that the work process perspective should be incorporated into the people analytics perspective and vice versa. This blending can provide additional layers of analysis. IS researchers have already proposed people analytics approaches that, e.g., rely on shop-floor process data (Wu & Hou, 2010; Yang et al., 2022). However, additional potential lies in an in-depth integration of the two perspectives, enabling both HRM and process management to identify inefficiencies, address challenges, and continuously improve outcomes. For example, Liu et al. (2022) propose a people analytics-based, social process management and Farboodi et al. (2024) design a virtual cellular manufacturing system fueled by people analytics insights. Moreover, IS researchers might want to investigate how a feedback loop can be created between people analytics and work process management. In their pioneering work, Strohmeier and Röhrs (2017) propose a conceptual modeling approach for HRM that can support the integration on a methodological level.

**Explore the positive potential for employees as active users** Existing IS research in the field of people analytics recognizes its ethical challenges (Giermindl et al., 2022) and suggests that concerns of employees and other stakeholders need to be mitigated (Bankins et al., 2022). While these critical accounts are valuable and highly important, there is also room for an optimistic perspective that has so far received relatively little attention. If implemented appropriately, people analytics may also be linked with a positive paradigm shift—namely moving away from viewing employees as quantifiable data objects, that are merely objects of analysis towards acknowledging their individuality, agency, and potential for growth (Gal et al., 2020). We suggest future IS research explore how people analytics systems can be designed and implemented to empower employees with greater agency and oversight. In an early study on this, Zieglmeier and Pretschner (2023) propose to integrate inverse transparency (how employers use employee data) into people analytics system design. Furthermore, IS researchers should investigate how people analytics could actively promote employees' growth, well-being, and long-term professional development, e.g., through tailored training (Di Prima et al., 2024) or personalized support (Pillai et al., 2024).

### Alignment of resources in people analytics (Table 7)

Beyond the (individual) development of HRM, data/technology, and employees as the resources involved in people analytics, our proposed integrative framework implies that it is also relevant to align and orchestrate these resources across the three dimensions strategy, operations, and knowledge and skills in order to support the generation of business value through people analytics. As our systematic review has revealed, existing research only selectively addresses the issue of alignment (see Table 2), e.g., at the intersection of HRM and data/technology on the knowledge and skills dimension (facilitating knowledge transfer between analytics experts and HR managers), at the intersection of data/technology and employees on the strategy dimension (establishing strategic and cultural fit), and at the intersection of data/technology and employees on the operations dimension (optimizing human-AI collaboration). Beyond that, some theoretical perspectives on people analytics and value creation exist in the current literature (as discussed above). While they are laudable and provide very relevant insights, also those works address the aspect of resource alignment mostly selectively or only indirectly. For example, in their influential work from the HRM research discipline proposing the LAMP framework, Marler and Boudreau (2017) mainly address alignment at the intersection of HRM and data/technology on the strategy and operations dimensions. In one of the theoretically most advanced works from the IS

**Table 7** Overview of research opportunities—alignment of resources in people analytics

| Research opportunities | Inspirational examples | Potential research questions |
|---|---|---|
| Investigate mechanisms and approaches of cross-resource alignment and orchestration | McCartney and Fu (2022a), Stelmaszak (2022), Werkhoven (2017) | Which mechanisms are at play in the alignment of resources in people analytics for business value creation?<br>Which processes are relevant and how should they be designed and organized for the alignment of resources in people analytics for business value creation (e.g., value alignment of involved actors)?<br>Which existing IS models from other fields are suitable to be developed further for the specific context of resource alignment in people analytics? |

discipline, Werkhoven (2017) mainly addresses alignment across resources on the knowledge and skills dimension and at the intersection of HRM and data/technology on the operations dimension. Therefore, we call for IS researchers to help advance further the understanding of mechanisms and approaches through which organizations can align their resources for business value creation in people analytics, by taking a more holistic perspective across resources and dimensions. Existing models from fields such as artificial intelligence (Enholm et al., 2022) and big data (Oesterreich et al., 2022) could be suitable points of orientation to support further theorizing in people analytics.

## Conclusion

In this paper, we have established an integrative framework and a research agenda for IS to help advance the field of people analytics (RQ3). It is based on a systematic literature review of 122 research papers from IS to understand the discipline's contribution to date (RQ2) and a bibliometric analysis of 1,682 research papers from within and beyond IS for cross-disciplinary context (RQ1). As we observe a divide of people analytics research into a predominantly technological and a predominantly managerial stream across disciplines, IS with its dual lens is generally well-positioned to help develop the field further. To date, IS researchers have developed innovative people analytics approaches (across nine research foci) for different HRM practices, particularly "hiring and firing" activities such as employee selection, allocation, and turnover prediction. IS researchers have also highlighted the importance of enabling factors that support the successful adoption of people analytics in organizations. These enablers can be categorized into stakeholder management, alignment of analytical and organizational perspective, and compliance and ethics. However, there is still room for more IS research at the intersection of technology and management. Therefore, we have synthesized our findings to propose an integrative framework and an IS research agenda. The framework of business value creation highlights the need to develop the three key resources involved in people analytics (HRM, technology/data, and employees) across the three dimensions of strategy, operations, and knowledge and skills. Furthermore, the framework implies that examining the synergies and tensions (alignment) between these resources is also relevant. The research agenda outlines potential research directions that address both the development of individual dimensions as well as their alignment. These directions include, but are not limited to, expanding the user perspective in people analytics systems design, strengthening a human-focused evaluation of people analytics approaches, blending people analytics and work process perspectives, and investigating mechanisms and approaches through which organizations can align their resources to create business value from people analytics.

Both the framework and the research agenda have implications for academic research and managerial practice. Our work shall inspire researchers to identify innovative research themes that might be of interest for future work, such as the emerging themes of unconventional data sources (Zazon et al., 2023), XAI (Gao et al., 2024), and generative AI (Parker et al., 2023) in HRM. It can help novice researchers in IS to find access to people analytics research and assist more experienced scholars in positioning their own research in the academic discussion. Editors and reviewers are supported in assessing the novelty of articles under review and whether they have sufficiently referenced the existing body of knowledge on people analytics in IS. Moreover, our paper shall advance the theoretical discourse on how people analytics can create business value. Complementing contributions such as Marler and Boudreau (2017), Stelmaszak (2022), and Werkhoven (2017), our proposed framework extends existing theory by taking a more holistic perspective and integrating the technological with the managerial perspective on people analytics. It further confirms and extends existing theory on value creation through HRM and IT in general. Practitioners may use our work to find references to the latest insights at the forefront of people analytics development. The framework can serve as a basic structure for organizations to plan, design, and implement people analytics initiatives tailored to their unique organizational contexts. By emphasizing the development and alignment of key resources across strategic, operational, and capability dimensions, it supports organizations in translating analytical efforts into measurable business value. Our paper thus helps bridge the gap between research and practice: while practitioners can use it as a reference for implementation, researchers can use it to identify and address aspects that are still under-researched—which in turn will lead to more insights to be used by practitioners in the future.

As for any review paper, our findings have limitations, which mainly stem from the methodologies of literature search and synthesis. First, although we conducted a systematic literature search, possibly not all relevant articles might have been identified. On the one hand, although we thoroughly selected the search terms based on existing literature, additional terms might have revealed further relevant papers. We tried to mitigate this issue by conducting a forward and backward search. On the other hand, while we cover major IS journals and conferences, the number of sources selected for our systematic review of IS literature is still limited. Second, while we conducted a structured bibliometric analysis to uncover patterns in the literature across disciplines, certain limitations and potential biases remain. After a careful review of available databases, we based our analysis on data extracted from Web of Science. However, relying on this single database may have introduced selection bias. Future research could address this limitation by integrating additional sources (e.g., Scopus or Google Scholar). Moreover, as with any bibliometric technique, the results are sensitive to the specific choice of algorithms and parameter settings (e.g., cluster resolution). While our settings were carefully selected and tested for interpretability and coherence, they represent one of several valid approaches. Different configurations might yield alternative clustering structures or thematic emphases. Third, our methodology for literature synthesis entails adapting a two-dimensional concept matrix (for the analysis of people analytics approaches), utilizing open coding techniques from grounded theory (for the identification of enablers for people analytics implementation), and finally employing steps of configurational theorizing (for the deduction of an integrative framework of business value creation). This approach does not represent the only possible way of synthesizing literature. However, our methodology yields a broad, transparent, and replicable synthesis of people analytics research. We hope our findings will help researchers and practitioners gain a thorough overview and better understanding of people analytics knowledge and stimulate further research in this fascinating field.

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