Divergent Conceptions of People Analytics in Practice versus Academia

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1 INTRODUCTION

In the last decade, the topic of people analytics has gained a lot of traction. Due to the increasing amount of attention, a lot of debates regarding conceptual definitions and practices have sprouted among experts[78]. The market is flooded with software meant to aid human resource managers, businesses, employees and other stakeholders in their quest for data-driven decision-making. In the last two decades, legal entities in the field have released more than 40 people analytics tools with usage ranging from human resources analytics and social network analytics to technical monitoring and employee surveillance[32]. To summarise their utility, these instruments serve as means of algorithmic decision-making in people-related organisational practices and challenges such as attrition, collaboration, hiring, retention, internal mobility, talent management, staffing, and others[80]. Sensibly, people analytics has become a topic that sparks significant interest in practice and academia. Apart from the increased development of HR analytics tools in the last decade, the amount of scientific publications has experienced a steep increase (Figure 1), with accentuated growth between 2016 and 2017, as well as 2018 and 2019[9]. To showcase the rising levels of attention the field receives, just a year later, in 2018, 84% of the Global Human Capital Trends survey participants claim that people analytics has provided invaluable insights and plays a pivotal role in workforce operations. Due to the overwhelmingly positive feedback, people analytics takes second in the 2018th HR trend ranking[16]. Despite the excitement among professionals, the existing literature is still in its early phases of development, and academics are still determining if the promises of evidence-based decision-making will be realised[50]. A lot of the publications in existence express scepticism and uncertainty towards PA, predominantly due to a lack of empirical data to back up the pompous aspirations of the field, unethical surveillance, and employee well-being[24][27][28][67]. Moreover, state-of-the-art practices involve a lot of ethically questionable practices such as unnecessary data storage, pending legal compliance, privacy and protection issues, overlooking employees' right to informed consent, and intrusive monitoring. Logically, such behaviour introduces risks to both the organisation and employees and leaves room for discrimination and profiling[75]. To further support the existence of these vulnerabilities, a survey conducted by Insight222 involving 57 companies unveils that 81% of participants stated that their projects in workforce analytics were occasionally or frequently jeopardised due to concerns about data ethics and privacy[58]. The literature reviewed suggests that the academic world requires further regulations and more empirical data to recognise the subfield of people analytics as a safe practice to utilise.

Evidently, there is a mismatch between practitioners' and academics' understanding of the people analytics concept; such discrepancies cause much debate on regulating and applying PA appropriately. Therefore, this paper provides tangible differences in concepts between practice and academia in the domain of people analytics. The importance of this thesis emerges from establishing the underlying dissimilarities between the two viewpoints, a valuable step forward to making space for further research on bringing academia and practice together. Consequently, this work strives to answer the question, "How do experts understand and utilise people analytics, and what are the key conceptual differences between academia and practice?". The question is addressed by reviewing relevant practitioners' publications, constructing a scheme that represents the gathered data, and comparing it with up-to-date academic work. Then, the derived results will be analysed, and critical concepts that differ amongst our target groups will be structured. By carrying out this investigation, the research aims to bridge the notable gap between theoretical insights and practical applications. Understanding these conceptual discrepancies will not only benefit scholarly research but also provide tips for organisations that wish to harness the full potential of people analytics in the form of state-of-the-art practices.

2 BACKGROUND

Unfortunately, providing a unanimous definition proves to be quite challenging due to the conflicting and ambiguous terminology among both scholars and experts. According to [81], people analytics is "A novel, quantitative, evidence-based, and data-driven approach to manage the workforce ". Others believe that "The continuous process of transforming and translating workforce data into organisational insights at varying levels of sophistication enables managers to make data-driven workforce decisions"[50] is a more suitable explanation of the term, while [79], for instance, states it is merely "a tool". For the rest of this paper, we will use [32] interpretation, which complies with most of the up-to-standard definitions provided by academic literature. They state that people analytics are "socio-technical systems and associated processes that enable data-driven (or algorithmic) decision-making to improve people-related organisational outcomes". Moreover, depending on the author and field, the terms: "people", "workforce", "workplace", "social", "HR", "Human Capital", "Employee", and "Talent" could be used interchangeably when accompanied with "analytics". As for the aspirations of PA, the branch promises to address challenges in the field of human resources management by utilising quantitative and qualitative methods, including regression, clustering, significance testing, interview and survey engineering.

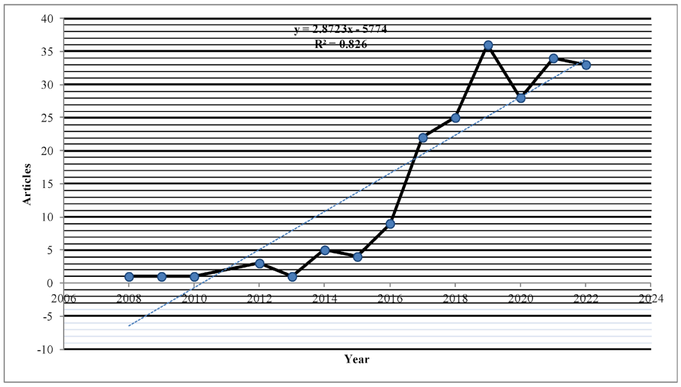

Figure 1: Annual Scientific Production [9]

To justify the significance of the research and the existence of conceptual differences, this paper offers more insights into the ongoing debate between academia and practice. An aspect of people analytics that has captured the attention of critics is the legitimate, ethical concern followed by employee surveillance and how inspection might influence the working class. Employee tracking has raised so many concerns in the academic world that scholars have rebuked it as evocative of Taylorism[32]. If such moral issues are not appropriately apprehended, it would not be a stretch to connect managers and George Orwell's dystopian character, "Big Brother" in the future. As an illustration,[82] claims that "The boundaries of employee monitoring and related analytics are being extended from employees' work lives to well into their social and even physiological spaces" (p. 63).To further impugn people analytics, scientists are uncertain whether underlying algorithms are not built on prejudice and biases[83], which, combined with excessive surveillance, leads to the elevated probability of drastically increased stress levels in employees. In 2015, for instance, Amazon came to the realisation that the recruitment engine they were using was systematically discriminating against female employees. The software was trained on resumes and other internally available materials on predominantly male employees. As a result, the ML (machine learning) algorithm displayed clear preferences towards men[15][75]. Last but not least, it has become apparent that very few organisations speak of tangible value and benefits upon the introduction of people analytics practices and tools[51][35][52][66]. For instance,[35]states, "Despite the recent popularity of workforce analytics, there is much that we do not yet know about the processes through which analytics affects the strategy execution process in organisations and, ultimately, firm success" (p. 680).

PA enthusiasts, however, claim that the main focus of the field is not on surveillance but, instead, it is about the approach of hypothetico-deductive reasoning[34]. Furthermore, despite the above-mentioned concerns, almost 70% of sizable businesses state they have a people analytics team and rank PA as a top priority [32]. For instance, Google's people analytics team has created an analytical approach to hiring using predictive analytics to determine a candidate's chances of success stemming from information relevant to each employee.[31]

Based on the still-increasing use of PA, the industry stands to gain a lot from the mutually beneficial relationship between academia and practice, which facilitates knowledge sharing and drives innovation.

3 METHODS

A crucial detail of this paper's methods and coverage is that it aims to stand on the shoulders of previous researchers and update the academic world with a general overview of the ongoing dispute between academia and practice regarding people analytics. As a courtesy of Dr Hüllmann, I have been given access to previous literature reviews in which work dates back to 2021 in the field of experts' publications and to February 2024 for scholarly materials. The search scope of this thesis will be limited to missing intel in the above-mentioned time frames. Having said that, an appropriate approach to analysing and finding the distinctions between practice and academia would be to perform an exhaustive literature review of the latest work on the topic and compare the motives occurring in both perspectives. This comparison will become apparent with the use of a well-defined coding approach, and finally, the implications will be discussed systematically.

3.1 Literature Search Strategy and Search Scope

This paper will perform a systematic literature review on recent publications in the domain of PA, which [40][41] defines as " a structured approach to identifying, evaluating, and synthesising research." The structured approach I have chosen was initially developed by [77] and covers four essential pillars defining the literature review's search scope. The taxonomy covers processes, sources, coverage, and techniques; each will be independently justified below. A clear depiction of the general approach is provided in Table 1.

1.	Process	Sequential
2.	Sources	Bibliographic databases; Publications
3.	Coverage	Representative
4.	Techniques	Keyword Search; Forward Search

Table 1: Definition of the Search Scope[77]

1. Process: Using a sequential approach would be the more appropriate of the two known approaches, sequential and iterative, due to the explicit sequence of steps the study undertakes. The phases build upon previous ones, consequently introducing new research once the analysis has commenced, which could introduce bias and errors. Therefore, a clear and once-occurring time frame has been set for the literature review, which aims to cover all relevant and up-to-date materials on the topic.

2. S ources: Due to already existing literature reviews, this study concerns itself only with practitioner work retrieved from nine leading consultancies: Deloitte, Capgemini, Accenture, McKinsey, KPMG, PwC, EY, BCG, and IBM. These firms offer a diverse set of publications that will aid the reader in grasping the expert's vision on the topic. They are also recognized authorities in their respective fields, providing relevant insights that are often cited and considered trustworthy by industry professionals and academics (Appendix A).

3. Coverage: A comprehensive approach would require a significant amount of time and resources, which are not feasible within the scope of this thesis. Furthermore, by choosing a representative coverage approach, the study will select a diverse range of samples that will capture essential variations and characteristics of the publications on the wide web. This will abide by the time constraints while allowing us to gain significant insight.

4. Techniques: This paper mainly relies on the general keyword search technique. Figure 2 clearly depicts the extensive keywords that serve as input to various search engines, where

precise checks in the paper's title, abstract, and body will be conducted, what consultancies will be studied and how the study process will be carried out. Due to the nature of the study, a forward search will also be implemented to ensure the review's rigorous claims. Forward search denotes the collection of appropriate and recent publications that have cited the work under review, otherwise known as "going forward in time" [84][85].

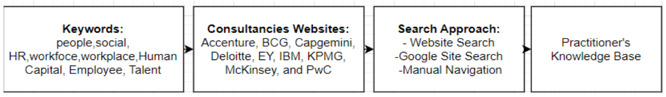

Figure 2: Search Process for Practiitioner's Literature

The search will be executed following and in accordance with the above-defined keywords and criteria. Initial results will be screened by title and abstract. Last, but not least, all PA results will be stored in a single file, where the entire body of the publications will be examined and filtered by relevance later. The practitioner's work will be considered relevant if it addresses algorithmic decision-making in the field of people processes. Source count will be performed before and after filtering and displayed in a table clearly stating the number of papers retrieved from each database or consultancy.

Following the above-mentioned strategy will provide this paper with a verified structure that scientifically finds discrepancies between scholars' and experts' conceptual definitions. Revising outdated analyses on differences between the two perspectives and passively presenting how the industry and related underlying concepts have changed over the last few years will contribute to the ongoing debate. Hopefully, this study will inspire further in-depth research to facilitate collaboration between the two parties and maximise benefits from this controversial topic.

3.2 Thematic Analysis

Once the literature review is completed, the findings gathered will be processed with a five-step thematic analysis, consisting of the following steps: 1. Transcription and selection of quotes; 2. Selection of keywords, 3. Coding, 4. Theme development, and 5. Conceptualisation through interpretation of themes and codes and development of conceptual models[55].

1. Transcription and selection of quotes: In the initial phase, I will familiarise myself with the already filtered relevant publications and choose key quotes that represent viewpoints on the study's objective
2. Selection of keywords: Once the familiarisation process is completed, keywords encapsulating recurring themes and patterns will be generated.
3. Coding Scheme: In the third step, the developed keywords will be used to form short phrases or words, also known as codes, that will capture the central theme of the data
4. Theme Development: Theme development consists of grouping the created codes in a meaningful way and then deriving meaning that links the data to the research question. For instance, the identified theme in the following quote: "*AI-enabled project management tools, for example, include powerful analytics that can help project managers anticipate delays and drops in productivity*" would be "*Artificial Intelligence*".
5. Conceptualisation through interpretation of themes and codes and development of conceptual model: In this step, the patterns found through codes and themes will be defined and justified. Then, the definitions will be systematically compared to already existing patterned meanings, encapsulating academic viewpoints. This process will generate a unique representation of the derived data, also known as a conceptual model, that embodies all the gathered insights and answers to the research question.

This well-established practice will allow us to break down PA into segments and discover apparent differences in underlying concepts upon examining the newly found data.

4 FINDINGS

The relevance filter on materials found in the literature review halved the articles used by this paper. The main reason is that most of the articles were broad, just hinting at the use of digital algorithmic HR tools, or were simply irrelevant. In case they had one, the initial research was based on adding all articles from these 9 consultancies with relevant titles and abstract sections. Articles titled *"Realising the power of technology + talent", for instance, simply stated, "...partner with HR and implement change management practices to introduce new ways of working in tandem with new technology, with customer-centric multidisciplinary teams helping to drive speed to market and enterprise platform teams to enable scale*"[64]were excluded from the literature review due to lack of specificity, proof and questionable relevance. A few articles were considered relevant to the research. However, PA's appliance, definition, or contribution could not identify a specific theme. Their inability to fit into the defined coding scheme led to the creation of the "other" concept. Such articles were considered in the study but will not be further analyzed. The resources that remained were split into 4 distinct categories: Motivation behind PA, Approaches towards achieving PA, Fields affected by people analytics, and Consequences from people analytics in the form of ethical and practical concerns. They were chosen in an attempt to cover the major topic in people analytics fully

Table 2: Coding Scheme

Concept	Theme	Reference
Motivation	Justification	[56]
	Purpose	[61]
	Definitions	[61]
Approaches	Cloud-Based Solutions	[57][3][1]
	Artificial Intelligence	[57][61][17][62][38][1][20][3][29][8][11][12][74][65][45][46][60][68][48][49][5][18][54][7][6][10][36][72][26][73][59][39][37][47]
	Machine Learning	[74][60][37][47]
	Virtual Reality	[2]
	Visual Analysis	[13][19][11][42][44]
	Qualitative Analysis	[61]
	Quantitative Analysis	[61]
	Predictive Analysis	[38]
	Applicant Tracking System(ATS)	[37]
	Human Capital Data Lake Algorithms	[71][43]
Affected Fields	Attrition	[30]
	Talent Management	[29][23]
	Employee Experience	[62][30][14][5]
	Retention	[42][23]
	Talent Acquisition and Staffing	[65][72][37]
	Training Effectiveness	[23]
	Diversity, Equity, Inclusion	[30]
Consequences	Privacy concerns	[30]
	Employee Privacy	[26]
	Data Quality	[48]
Other	Miscellaneous	[87][19][11][60]

and provide an overview of specific field parts that are viewed differently between academia and practice. Table 2 demonstrates the identified concepts and themes retrieved from the review

4.1 Motivation

Most of the papers in this study have dedicated a section contributing towards the motivation behind and purpose of people analytics as a practice; however, most lack justification and clarity of their claims and/or are missing a definition of the field. An example would be: “However, this reorientation requires Modern HR leaders who can solve the right problems in innovative, tech-forward ways and reshape how work is done in their organisations.”[69] Therefore, in the coding scheme, I have handpicked only articles that clearly state what people analytics is about and how it could be beneficial to a legal entity. Judging by the results produced in Table 2, it has become apparent that practitioners tend to avoid providing a comprehensive and clear definition of people analytics while justifying the importance of PA with no evidence to back up such claims. For example, “*Data is growing fast, and technologies—AI, ML, RPA, and so on—if applied smartly, have the potential to help you validate, structure, and better use it. Deloitte sees these collectively as the next step in humans with machines collaboration*”.[57]

4.2 Approaches

The approaches section is central to the organisation of the developed coding scheme. It comprises an exhaustive list of all the different approaches encountered in the 79 practitioner texts that are covered in this study. Without a shred of a doubt, the majority of the articles have focused solely on the technological boom surrounding artificial intelligence and machine learning, as almost 50 per cent of the quotes extracted from all articles are AI-related. Other less popular methods involve visual analysis in the form of dashboards, virtual reality, cloud-based solutions and others. As displayed by the coding scheme, various approaches could be encountered in publications. Some concepts overlap, such as predictive analysis and machine learning. It is worth noting that this overlap arises in order to demonstrate how rarely authors of publications use narrowed-down, specific approaches and, consequently, how often they follow global and local trends and write in a broad and unspecific style to attract a bigger audience. This becomes apparent when a comparison is made between the number of articles related to virtual reality and AI, especially when, today, artificial intelligence could span from virtual reality to AI-integrated cloud solutions. Another plain observation would be that a decent percentage of the articles(no matter the topic) had a call-to-action component. An example would be, “Our experienced advisors are happy to introduce the (people analytics)solution for you in-depth via a demo environment.”[86] This suggests that some of the articles are written for marketing purposes rather than truth-seeking, which would rarely be the case in academic writing. Another instance of this occurrence would be, “...*With next-gen AI and automation, such as GenAI-powered software engineering automation, Capgemini is at the forefront of disruptive innovation.*”[38]

4.3 Affected Fields

The affected fields list sectors of HR and BPM that altered the approaches mentioned above. However, this section of the coding scheme is not exhaustive, as many relevant quotes were removed after the initial review due to a lack of credentials or a publication date that falls outside the study's reach. In summary, it is rather apparent that the beneficiaries are predominantly People Management Processes such as staffing, training and attrition, where employee experience seems to be the most recognised and affected by the PA field, according to my research. Recruiting is second to top, influenced by new AI-augmented data-driven approaches to hiring.

4.4 Consequences

Surprisingly, very few articles covered practical consequences and concerns. Furthermore, not only was the total number of encounters of concerns in the field of PA low, but the mentioned concerns were introduced in a few sentences and covered only privacy and data quality concerns. The depth and intricacies of the academic’s reservations were almost entirely missing in the practitioners’ message. Therefore, this study reveals that practitioners are systematically likely to either be unaware, ignorant, or unbothered by potential threats in the world of data, judging by the fact that there are too few occasions in which a component of the article is dedicated to possible concerns or violations. In their efforts to sell their services and gain credibility, consultancies might eventually suffer from only giving voice to only one side of the story. Naturally, people analytics has advantages and disadvantages; however, in this study, three publications included possible repercussions of the practice or any other relevant insight on PA’s drawbacks. Practitioners, driven by ulterior motivations(marketing their agencies, selling their products), falsely appear to be quite optimistic about making people analytics a standard procedure in business. In reality, however, they fail to consider the consequences PA might inflict.

5 DISCUSSION

This section of the paper will compare the concepts derived from the coding scheme to recurring themes seen in academic literature. This approach will contribute to establishing the hidden barriers between academia and practice and provide relevant insights on how to tear said barriers down while leaving space for further research. I will individually cover each concept I have adopted in the coding scheme, where some sections will be shorter due to an aligned understanding between scholars and practitioners.

5.1 Motivation

Even though reaching a unanimous decision when considering the definition of people analytics is challenging among stakeholders. More often than not, academics and professionals come to an agreement on the justification and purpose of PA and the further development of the unrealized sector. For most, people analytics is a data-driven algorithmic approach that extracts and analyses people-related data, a necessity in the day and era of big data. Unlike in academic writing, a clear definition or motivation is often absent in the publications of professionals. However, all relevant parties are united in their aspirations to extract value from data in people-oriented processes and agree that PA could be invaluable if incorporated appropriately. Furthermore, the justification and purposes of PA seem to align with those of scholars and practitioners. For instance, a comparison could be made between the following quotes from academia and practice. According to Deloitte, "People analytics interventions can improve business performance, provide a better workforce experience, and enable a data-driven HR."[61], meanwhile, Tina Peeters claims that "People analytics can thus be used to solve pressing business issues, as illustrated, for example, by the people analytics team of ING…They were consequently able to determine which employees would fit the profile of the vacancies well, and conversations with those employees ensued".[88]

5.2 Approaches

In the previous section, different motivations were listed as plausible reasons why consultancies would prefer to use and advertise a certain approach of the field of people analytics. These findings point out the conceptual difference of advertising certain aspects of PA in a biased and unfounded manner in order to extract benefits for the consultancy. Such marketing promises truly defy the curiosity-driven approach of scholars and could cause suspicion among experts with technical backgrounds due to their broadness. Even though scholars also attempt to gain more citations and relevance, their best marketing strategy would be producing scientifically sound and accurate work. Contrary to this, the tendency to introduce hype around a problem only the consultancy can solve via a new "revolutionary" software is common in the professional world. An instance of such marketing would be *"Deloitte's Human Capital professionals leverage research, analytics, and industry insights to help design and execute the HR, talent, leadership, organization, and change programs that enable business performance through people performance."*[89]. According to the study, another important discrepancy between practice and academia is the extent to which practitioners follow trends. The table clearly shows that most articles focus on artificial intelligence, ML, cloud-based solutions, and other currently trending topics. This verifies the theory that practitioners rapidly adopt innovative technology and strive to be the first to extract value from it. This, however, is sometimes at the expense of proven, reliable methods. Scientists, on the other hand, tend to prefer proven and empirically tested approaches.[90] Finally, practitioners appear to use simple and non-specific language in order to reach as many people as possible and convert them into clients. Principles regarding people analytics were briefly mentioned but not fully explained and lacked depth, which is rarely true in academic writings. An example you are already familiar with is Capgemini's claim: *"With next-gen AI and automation, such as GenAI-powered software engineering automation, Capgemini is at the forefront of disruptive innovation."* It provides no further intel on exactly how this was achieved.

5.3 Affected Fields

Scholars and practitioners seem to agree regarding the fields that people analytics affect, listing all people-related processes and some business processes as direct beneficiaries of PA.

5.4 Consequences

Even though the value and benefits people analytics can bring to the world of data are recognized and appreciated, scholars lack data and claim the field is too early in its development to be labelled as trustworthy[91]. Uncalculated liabilities might occur in the daily use case of PA, and that is something practice seemingly forgets to mention. According to the data extracted from the research, that perhaps is the most crucial conceptual difference between academia and practice. Neglecting ethical concerns arising from the active use of people analytics might lead to bad employee experience, unwanted surveillance, privacy leaks and discrimination and bias due to data contamination. Regarding the few thematic concerns identified in the coding scheme, data quality was the only structural concern explained, and the consequences of ignoring the data quality for the organization were also discussed. Academics, on the other hand, spend a vast majority of their time producing work that critically reviews existing literature on people analytics in an effort to establish the advantages and disadvantages of utilizing PA. Empirical knowledge is gathered through experiments, and based on them, entire sections are dedicated to practical concerns. When practitioners leave out such important information, they sound untastefully optimistic, and such practices quickly diminish their work's credibility and scientific pursuit.

6 CONCLUSION

In this paper, a study was conducted on 133 publications produced by nine of the leading consultancies in the world. The literature review was later limited to 79 papers due to issues of relevance and lack of authorship and date of publication. This paper aims to establish conceptual differences between academia and practice in the field of people analytics. We have grasped a few such discrepancies that could be responsible for most of the disagreements between scholars and practitioners. In our findings, we uncovered that practitioners follow trends and make what appear to be unjustified promises due to the broadness of their language, striving to sell their product and gain relevance and credibility. Later, I commented on how the extracted data pointed out that this false optimism and lack of depth and information on practical concerns in practitioners' research are the most prominent and significant conceptual differences. Due to time and resource constraints, the discrepancies covered are far from exhaustive, and a lot of data was dismissed due to the relevance and trustworthiness of the publications. Another flaw to consider is that the study could potentially be biased as the coding scheme was developed with no peer review, meaning that the quotes, keywords and concepts I chose and developed have not been revised. This study also aims to contribute to the discussion of people analytics by bringing forward relevant insight and eventually supporting and inspiring future research on the topic.

REFERENCES

1. Accenture. (2023). Technology Vision 2023 for Biopharma.
2. Accenture. (2022). Turning virtual experiences into expertise: Caseworker training reimagined.
3. Accenture. (2021). Setting up for skilling up: Henkel's smart bet for innovation and growth from sustained upskilling efforts.
4. Bachman, C., Several, A., & Wrigth, D. (2015). Deloitte and SuccessFactors Workforce Analytics & Planning for Federal Government. Deloitte Development LLC.
5. Baier, J., Twesten, M., & Maini, P. (2024, April 9). The path to digital Maturity in HR. BCG Global. https://www.bcg.com/capabilities/people-strategy/digital-human-resources/digital-maturity-in-human-resources
6. Baier, J., Beauchene, V., Bedard, J., Caye, J.-M., Kolo, P., Ruan, F., Alonso, A., Ariganello, A., Helfritz, K., Morton, B., Wees, L. V., Wong, W., & Járegui Morales, J. (2023). Creating People Advantage 2023. https://web-assets.bcg.com/09/dd/e54702c54eacb645f8301af18518/bcg-creating-people-advantage-2023-nov-2023-r.pdf
7. Bedard, J., Lavoie, K., Laverdiere, R., Bailey, A., Beauchene, V., & Baier, J. (2024, May 30). How Generative AI will transform HR. BCG Global. https://www.bcg.com/publications/2023/transforming-human-resources-using-generative-ai
8. Bérubé, V., Maor, D., Ocampo, M., & Sukharevsky, A. (2023, June 27). HR rewired: An end-to-end approach to attracting and retaining top tech talent. McKinsey & Company. https://www.mckinsey.com/capabilities/people-and-organizational-performance/our-insights/hr-rewired-an-end-to-end-approach-to-attracting-and-retaining-top-tech-talent
9. Bonilla-Chaves, E. F., & Palos-Sánchez, P. R. (2023). Exploring the Evolution of Human Resource Analytics: A Bibliometric study. Behavioral Sciences, 13(3), 244. https://doi.org/10.3390/bs13030244
10. Brandt, E. (2022, September 21). Moving beyond spreadsheets with IBM Planning Analytics. IBM Blog. https://www.ibm.com/blog/moving-beyond-spreadsheets-with-ibm-planning-analytics/
11. Brian. (2024, May 6). Increasing Your Return on Talent: The Moves and Metrics that Matter | McKinsey. BrianHeger.com. https://www.brianheger.com/increasing-your-return-on-talent-the-moves-and-metrics-that-matter-mckinsey/
12. Brassey, J., De Smet, A., Field, E., Lauricella, T., & Weddle, B. (2024, May 8). To defend against disruption, build a thriving workforce. McKinsey & Company. https://www.mckinsey.com/capabilities/people-and-organizational-performance/our-insights/to-defend-against-disruption-build-a-thriving-workforce
13. Capgemini. (2022). REINVENT TALENT ACQUISITION AND EMPLOYEE EXPERIENCE.
14. Damonte, A., Ledet, E., Morales, D., & Tobey, S. (2023, May 2). The next competitive advantage in talent: Continuous employee listening. McKinsey & Company. https://www.mckinsey.com/capabilities/people-and-organizational-performance/our-insights/the-next-competitive-advantage-in-talent-continuous-employee-listening
15. Dastin, J. (2022). Amazon Scraps Secret AI Recruiting Tool that Showed Bias against Women *. In Auerbach Publications eBooks (pp. 296–299). https://doi.org/10.1201/9781003278290-44
16. Deloitte Insights (2018), "The rise of the social enterprise. 2018 deloitte global human capital trends", 8 May, available at: https://www2.deloitte.com/content/dam/insights/us/articles/HCTrends2018/2018-HCtrends_Rise-of-the-social-enterprise.pdf (accessed 3 March 2021).
17. Deloitte Touche Tohmatsu India LLP. (2023). People Analytics. In People Analytics.
18. Dhar, J. (2024, May 29). People strategy in the age of generative AI. BCG Global. https://www.bcg.com/publications/2023/people-strategy-for-digital-age-of-ai
19. Dutta, A., Gardner, N., McConnell, M., & Sinisterra-Woods, A. (2023, July 5). Transforming public sector hiring with data-enabled talent 'win rooms' McKinsey & Company. https://www.mckinsey.com/industries/public-sector/our-insights/transforming-public-sector-hiring-with-data-enabled-talent-win-rooms
20. Elevating EX to keep up with disruption. (2024). Accenture. https://www.accenture.com/ro-en/blogs/business-functions-blog/elevating-employee-experience
21. Espegren, Y. and Hugosson, M. (2023), "HR analytics-as-practice: a systematic literature review", Journal of Organizational Effectiveness: People and Performance, Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/JOEPP-11-2022-0345
22. EY. (2023, May 12). How Yara centralized their HR operations. EY - Netherlands. https://www.ey.com/en_nl/consulting/how-yara-centralized-their-hr-operations
23. Finio, M. (2024, April 4). Business process management (BPM) examples. IBM Blog. https://www.ibm.com/blog/business-process-management-examples/
24. Gal, U., Jensen, T. B., & Stein, M. K. (2020). Breaking the Vicious Cycle of Algorithmic Management: A virtue Ethics Approach to People Analytics. Information and Organization, 30(2), 100301. https://doi.org/10.1016/j.infoandorg.2020.100301
25. Gierlich-Joas, M., & Hüllmann, J. A. (2022). Tensions between Affordances and Valuations of People Analytics among Stakeholders. In Proceedings of the Pre-ICIS 2022, International Workshop on The Changing Nature of Work, Copenhagen, Denmark
26. Goldstein, J. (2023, October 5). HR and talent in the era of AI. IBM Blog. https://www.ibm.com/blog/hr-and-talent-in-the-era-of-ai/
27. Guenole, N., & Feinzig, S. (2016). Decoding Workforce Analytics: A Simple Guide to Research Design and Analytics. IBM Smarter Workforce.
28. Guenole, N., Feinzig, S., Green, D., & Zhang, H. (2017). HR Analytics Readiness. IBM Smarter Workforce
29. Hancock, B., & Yee, L. (2023, June 5). Generative AI and the future of HR. In McKinsey & Company. McKinsey. https://www.mckinsey.com/capabilities/people-and-organizational-performance/our-insights/generative-ai-and-the-future-of-hr
30. Hancock, B., & Schaninger, B. (2022, February 24). Talent at a turning point: How people analytics can help. In McKinsey &

Company. https://www.mckinsey.com/capabilities/people-and-organizational-performance/our-insights/talent-at-a-turning-point-how-people-analytics-can-help

31. Harris, J.G., Craig, E. and Light, D.A. (2011), "Talent and analytics: new approaches, higher ROI", Journal of Business Strategy, Vol. 32 No. 6, pp. 4-13, doi: 10.1108/02756661111180087.
32. Hüllmann, J. A., & Mattern, J. (2020). Three Issues with the State of People and Workplace Analytics. In Proceedings of the 33rd Bled eConference, BLED 2020: Enabling technology for a sustainable society (pp. 1-14). University of Maribor. https://www.joschka-huellmann.net/publications/2020-05-20-draft-people-analytics-issues-short-v5-revised.pdf
33. Hüllmann, J. A., Krebber, S., & Troglauer, P. (2021). The IT Artifact in People Analytics: Reviewing Tools to Understand a Nascent Field. In F. Ahlemann, R. Schütte, & S. Stieglitz (Eds.), Innovation Through Information Systems: Volume III: A Collection of Latest Research on Management Issues (1 ed., Vol. 2, pp. 238-254). (Lecture Notes in Information Systems and Organisation; Vol. 48). Springer. https://www.joschka-huellmann.net/publications/2020-12-29-draft-it-artifact-formatted-v06.pdf
34. Hüllmann, J. A. (2022). Reconciling the Debate on People Analytics in Academia and Practice. In 35th Bled eConference – Digital Restructuring and Human (Re)action (pp. 539-554)
35. Huselid, M.A. (2018), "The science and practice of workforce analytics: introduction to the HRM special issue", Human Resource Management, Vol. 57 No. 3, pp. 679-684, doi: 10.1002/hrm.21916
36. IBM Corporation & Oxford Economics. (2023). IBM - State of SAP survey.
37. IBM Education (2023, November 13). AI in recruitment. IBM Blog. https://www.ibm.com/blog/ai-in-recruitment/
38. ISG recognizes CapGemini as a leader in intelligent automation across the US and Europe - CapGemini. (2024, March 8). Capgemini. https://www.capgemini.com/news/analyst-recognition/isg-recognizes-capgemini-as-a-leader-in-intelligent-automation-across-the-us-and-europe/#:~:text=According%20to%20ISG%2C%20Capgemini's%20intelligent,monitoring%2C%20integration%2C%20analytics%2C%20and
39. Jackson, N. (2023, August 1). How IBM HR and the Chief Data Office partnered to drive data quality, increased productivity and a move to higher value work. IBM Blog. https://www.ibm.com/blog/how-ibm-hr-and-the-chief-data-office-partnered-to-drive-data-quality-increased-productivity-and-a-move-to-higher-value-work/
40. Kitchenham, B. (2004). Procedures for performing systematic reviews (technical report). Keele University and National ICT Australia Ltd. Retrieved from http://www.inf.ufsc.br/~awangenh/kitchenham.pdf.
41. Kitchenham, B., Brereton, O. P., Budgen, D., Turner, M., Bailey, J., & Linkman, S. (2009). Systematic literature reviews in software engineering—a systematic literature review. Information and Software Technology, 51(1), 7-15.
42. KPMG. (2022). Optimizing the workforce during an economic downturn. In The Modern C-Level Executive: Thoughtful. Talent-Focused. [Report].
43. KPMG International, & KPMG. (2023). How to combine people and tech to turn people data into insight.
44. KPMG LLP. (2023). What is a Human Capital Diagnostic? https://info.kpmg.us/news-perspectives/industry-insights-research/2022-american-worker-survey.html
45. KPMG LLP. (2024). Data-driven HR evolution: Harnessing the power of people analytics.
46. KPMG LLP. (2024b). Measure employee behavior, not just sentiment, to drive successful transformation. https://kpmg.com
47. Lazar, D., & McGeein, M. (2024, March 12). IBM emerges as a Leader in the Forrester WaveTM for Digital Operations Planning and Analytics, Q4 2023. IBM Blog. https://www.ibm.com/blog/announcement/ibm-emerges-as-a-leader-in-the-forrester-wave-for-digital-operations-planning-and-analytics-q4-2023/
48. Locher, A. (2024, February 19). How to harness the value of people data and operational HR insights. EY – Switzerland. https://www.ey.com/en_ch/workforce/how-to-harness-the-value-of-people-data-and-operational-hr-insights
49. Locher, A., & Staiger, I. (2022, September 27). How can people analytics put humans at the center of your ESG strategy? EY – Switzerland. https://www.ey.com/en_ch/workforce/how-can-people-analytics-put-humans-at-the-center-of-your-esg-strategy
50. McCartney, S. and Fu, N. (2022), "Promise versus reality: a systematic review of the ongoing debates in people analytics", Journal of Organizational Effectiveness: People and Performance, Vol. 9 No. 2, pp. 281-311. https://doi.org/10.1108/JOEPP-01-2021-0013
51. Marler, J.H. and Boudreau, J.W. (2017), "An evidence-based review of HR analytics", International Journal of Human Resource Management, Routledge, Vol. 28 No. 1, pp. 3-26, doi: 10.1080/09585192.2016.1244699.
52. McIver, D., Lengnick-Hall, M.L. and Lengnick-Hall, C.A. (2018), "A strategic approach to workforce analytics: integrating science and agility", Business Horizons, Kelley School of Business, Indiana University, Vol. 61 No. 3, pp. 397-407, doi: 10.1016/j.bushor.2018.01.005
53. MIT Sloan School of Management. (2019). Human capital as a service: Humanizing the employee experience. In Interaction Analytics (p. 22).
54. Mourtada, R., Littig, L., & Bruehwiler, R. (2024, March 20). Unlocking AI at Work: Optimism and Concern from the ME Talent Market. BCG Global. https://www.bcg.com/publications/2023/unlocking-ai-at-work-implications-for-the-me-talent-market
55. Naeem, M., Ozuem, W., Howell, K., & Ranfagni, S. (2023). A Step-by-Step Process of Thematic Analysis to Develop a Conceptual Model in Qualitative Research. International Journal of Qualitative Methods, 22. https://doi.org/10.1177/16094069231205789
56. Nawrat, A. (2021, September 28). BCG: Only 37% of organizations have the right digital tools. UNLEASH. https://www.unleash.ai/hr-technology/bcg-only-37-of-organizations-have-the-right-digital-tools/
57. O'Dwyer, J., Deloitte, & Perricos, C. (2021). Artificial Intelligence & Data. In Deloitte.
58. Petersen, D. (2018), "Data ethics: 6 steps for ethically sound people analytics", Visier, available at: https://www.visier.com/clarity/six-steps-ethically-sound-people-analytics/ (accessed 3 March 2021).
59. O'Brien, K. (2024, May 15). Upskilling and reskilling for talent transformation in the era of AI. IBM Blog. https://www.ibm.com/blog/ai-upskilling/
60. PricewaterhouseCoopers. (2024). PWC's 2024 Digital Trends in Operations Survey. PwC. https://www.pwc.com/us/en/services/consulting/business-transformation/digital-supply-chain-survey.html
61. Razdan, N., Kaur, J., & Deloitte India. (2022). People Analytics Maturity in India - 2022.
62. Razdan, N., Sachdeva, J. K., & Deloitte India. (2023). People Analytics Maturity Report. In People Analytics Maturity Report. https://www2.deloitte.com/content/dam/Deloitte/in/Documents/Consulting/in-hc-people-analytics-16-10-noexp.pdf
63. Reinvent HR: Steer your firm in new directions | Accenture. (2023). https://www.accenture.com/us-en/blogs/business-functions-blog/hr-reinvention
64. Renker, K. (2024). Digital Supply Chain Future Workforce | Accenture. https://www.accenture.com/us-en/insights/supply-chain-operations/digital-future-supply-chain-workforce
65. Rhampton, J. (2023, August 9). (30) People Analytics – The future of knowing analytics about your team | LinkedIn. LinkedIn.

https://www.linkedin.com/pulse/people-analytics-future-knowing-your-team-john-rampton-2c/

66. Schiemann, W.A., Seibert, J.H. and Blankenship, M.H. (2018), “Putting human capital analytics to work: predicting and driving business success”, Human Resource Management, Vol. 57 No. 3, pp. 795-807, doi: 10.1002/hrm.21843
67. Schwieters, N. (2015). Ten Digital Trust Challenges (Issue December 2015). PwC
68. Sears, J. (2023, October 9).How artificial intelligence can augment a people-centered workforce .https://www.ey.com/en_gl/insights/workforce/how-artificial-intelligence-can-augment-a-people-centered-workforce
69. Shook, E., & Rodriguez, D. (2020, September 23). Personalising talent management strategy for Growth. Accenture.https://www.accenture.com/cr-en/insights/future-workforce/employee-potential-talent-management-strategy
70. Simón, C., & Ferreiro, E. (2017). Workforce analytics: A case study of scholar–practitioner collaboration. Human Resource Management, 57(3), 781–793. https://doi.org/10.1002/hrm.21853
71. Solow, M. & Deloitte. (2022). People Analytics as a service. In Deloitte Human Capital Data Lake [Report]. https://www2.deloitte.com/us/en.htmls
72. Stryker, C. (2024, April 17). What is Recruiting Automation? | IBM. https://www.ibm.com/topics/recruiting-automation
73. Stryker, C. (2024, March 18). 6 ways the recruitment process is boosted by AI. IBM Blog. https://www.ibm.com/blog/recruitment-process/
74. Talent. (2024, April 15). McKinsey & Company. https://www.mckinsey.com/capabilities/people-and-organizational-performance/how-we-help-clients/talent
75. Tursunbayeva, A., Pagliari, C., Di Lauro, S. and Antonelli, G. (2022), "The ethics of people analytics: risks, opportunities and recommendations", Personnel Review, Vol. 51 No. 3, pp. 900-921. https://doi.org/10.1108/PR-12-2019-0680
76. Tursunbayeva A., Di Lauro S., Pagliari C. (2018). People analytics—a scoping review of conceptual boundaries and value propositions. International Journal of Information Management, 43(5), 224–247. https://doi-org.ezproxy2.utwente.nl/10.1016/j.ijinfomgt.2018.08.002
77. vom Brocke, Jan; Simons, Alexander; Riemer, Kai; Niehaves, Bjoern; Plattfaut, Ralf; and Cleven, Anne (2015) "Standing on the Shoulders of Giants: Challenges and Recommendations of Literature Search in Information Systems Research," Communications of the Association for Information Systems: Vol. 37, Article 9. Available at: http://aisel.aisnet.org/cais/vol37/iss1/9
78. Chen, J., Cheng, C., Collins, L., Chharbria, P., & Cheong, H. (2018). The Rise of Analytics in HR: The era of talent intelligence is here. LinkedIn Repor
79. Cheng, M. (2017). Causal Modeling in HR Analytics: A Practical Guide to Models, Pitfalls, and Suggestions. Academy of Management Proceedings, 2017(1), 17632. https://doi.org/10.5465/AMBPP.2017.187
80. McAfee, A., & Brynjolfsson, E. (2012). Big data: the management revolution. Harvard Business Review, 90(10), 60–68.
81. Giermindl, L. M., Strich, F., Christ, O., Leicht-Deobald, U., & Redzepi, A. (2022). The dark sides of people analytics: reviewing the perils for organisations and employees. European Journal of Information Systems. Taylor and Francis Ltd. https://doi.org/10.1080/0960085X.2021.1927213
82. Khan, Shaji & Tang, Jintong. (2016). The Paradox of Human Resource Analytics: Being Mindful of Employees. Journal of General Management. 42. 57-66. 10.1177/030630701704200205.
83. Gal, U., Jensen, T. B., & Stein, M. K. (2017). People Analytics in the Age of Big Data: An Agenda for IS Research. Proceedings of the International Conference on Information Systems (ICIS), 1–11.
84. Levy, Yair & Ellis, Timothy. (2006). A Systems Approach to Conduct an Effective Literature Review in Support of Information Systems Research. International Journal of an Emerging Transdiscipline. 9. 10.28945/479.
85. Webster, Jane & Watson, Richard. (2002). Analyzing the Past to Prepare for the Future: Writing a Literature Review. MIS Quarterly. 26. 10.2307/4132319.
86. Predictive People Analytics Dashboard | Deloitte Hungary. (n.d.). Deloitte Hungary. https://www2.deloitte.com/hu/en/pages/human-capital/solutions/predictive-people-analytics-dashboard.html
87. Goldstein, J. (2023, August 11). New IBM study reveals how AI is changing work and what HR leaders should do about it. IBM Blog. https://www.ibm.com/blog/new-ibm-study-reveals-how-ai-is-changing-work-and-what-hr-leaders-should-do-about-it/
88. Peeters, T., Paauwe, J. and Van De Voorde, K. (2020), "People analytics effectiveness: developing a framework", Journal of Organizational Effectiveness: People and Performance, Vol. 7 No. 2, pp. 203-219. https://doi.org/10.1108/JOEPP-04-2020-0071
89. Fineman, D. R. (2017, February 27). People analytics: Recalculating the route | Deloitte. Deloitte Insights. https://www.deloitte.com/global/en/our-thinking/insights/topics/talent/human-capital-trends/people-analytics-in-hr.html
90. Goldsmith, J., & Vermeule, A. (2002). Empirical Methodology and Legal Scholarship. The University of Chicago Law Review, 69(1), 153–167. https://doi.org/10.2307/1600351
91. Loi, M., Oliver Suchy, Isabelle Schömann, Marco Bentivogli, Michele Carrus, & Wolfgang Kowalsky. (2020). People Analytics must benefit the people. An ethical analysis of data-driven algorithmic systems in human resources management. Algorithm Watch, 2. https://algorithmwatch.org/en/wp-content/uploads/2020/03/AlgorithmWatch_AutoHR_Study_Ethics_Loi_2020.pdf

A Appendix A

Search Results for Consultancies	Before Filter	After Filter
Deloitte	18	12
Capgemini	7	4
Accenture	21	12
McKinsey	12	10
KPMG	19	8
PwC	10	5
EY	12	7
BCG	11	9
IBM	23	12
Total:	133	79