Reconciling the Debate on People Analytics in Academia and Practice

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Abstract People analytics depicts the algorithmization of human resources management characterized by the data-driven automation and support of people-related processes or tasks. On the one hand, people analytics promises productivity increases through optimizing workforce planning, hiring, or talent development. On the other hand, the extensive data collection and analysis of employees' behaviors can be perceived as invasive, raising privacy concerns. This debate cannot only be explained by diverging norms and values, for example, practitioners realizing commercial opportunities while being criticized by academic commentaries. Instead, an alternative explanation suggests that the opposing views can be reconciled by diving into the conceptual differences regarding what analytical methods and data sources people analytics entails. Hence, this paper proposes the conceptions of operational and strategic people analytics based on a literature review of academics' and practitioners' literature. Four propositions about these conceptions' privacy and performance implications are derived. Future research should empirically validate these propositions.

Keywords: people analytics, criticism, conceptions, strategy, operations.

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1 Introduction: The Hype around People Analytics

People analytics is a hype topic seeing rising attention in professional practice (Chen et al., 2018). Practitioners popularize the topic with increasing availability of tools and functionalities, for example, AI-based video assessments, or consultancies, such as IBM or McKinsey, selling evidence-based hypothetico-deductive analyses for the human resources function (Hüllmann et al., 2021). People analytics describes the algorithmization of decision-making in people-related organizational processes such as hiring, retention, or staffing. Technological advances, unprecedented data availability, and cultural changes that consider humans as "walking data generators" drive the topic (McAfee & Brynjolfsson, 2012). Understandably, people analytics sparks considerable controversy and is being discussed in mainstream media (Ajunwa, 2019) and academic outlets (Gal et al., 2017; Tursunbayeva et al., 2021).

Critics reject people analytics on the grounds of unethical surveillance and privacy invasion through fine-granular tracing of employee activity. They slander people analytics as reminiscent of the dystopian Taylorism (Hüllmann & Mattern, 2020). Others question the construct and external validity of people analytics' methods. They claim there is little empirical evidence for the promised outcomes (Marler & Boudreau, 2017). It is suggested that the employees affected by people analytics suffer negative consequences due to discrimination through the underlying algorithms and data sources, which reproduce existing stereotypes and biases (Gal et al., 2017). Further negative consequences of people analytics include stress due to a pressure to perform, resulting from the "transparent employee" (Hafermalz, 2021). Proponents of people analytics praise the data-driven and seemingly objective decisions that lead to more effective human resources management. Examples include improving retention rates and reducing employee attrition, stronger talent management, and lean human resources processes on the operational level (Marler & Boudreau, 2017). Levenson (2018) claims that people analytics supports strategy execution, resulting in competitive advantage through long-term workforce planning.

Are the reasons for these opposing viewpoints on people analytics simply a result of different values and norms, for example, the privacy invasion is acceptable if it leads to improved organizational outcomes? It is questionable that leading academic institutions such as Harvard Business Review would endorse such approaches

(Leonardi & Contractor, 2018; Levenson, 2018). Perhaps, the controversy can be explained by practitioners realizing commercial opportunities and selling ethically problematic information systems? Although some practitioners do this, certainly not all of them can be accused of this, for example, Microsoft and IBM are engaging in people analytics while conforming to their respective privacy legislations (Hüllmann et al., 2021).

This paper puts forward an alternative explanation. It suggests that this controversy can be explained partially by diverging conceptions regarding what analytical methods and data sources people analytics entails. Conceptions are the underlying implicit assumptions and mental representations that people have in mind for people analytics (Laurence & Margolis, 1999). For example, software vendors focus on automating single human resources tasks via artificial intelligence and other computational approaches based on individual employees' behavioral data. In contrast, consultancies concentrate on the abstract idea of data-driven human resources management, including strategic decision-making regarding the workforce based on aggregated data and hypotheses tests. So far, only broad conceptions of people analytics have been put forward that do not sufficiently demarcate these conceptual differences in detail. For example, Hüllmann and Mattern (2020) define people analytics as "*socio-technical systems and associated processes that enable data-driven (or algorithmic) decision-making to improve people-related organizational outcomes.*" Such a broad definition cannot capture the necessary differences in data sources and analytical methods of people analytics that influence how experts perceive the topic. Hence, this paper asks the research question: ***How can the diverging conceptions of people analytics explain and reconcile the opposing viewpoints?***

This paper reconciles the controversy of people analytics by diving into the conceptual assumptions underlying the term, elaborating on what analytical methods and data sources are employed in practice. These assumptions are compared with the conceptions espoused by critical academic commentaries. Although the different conceptions cannot explain all of the controversy surrounding people analytics, the reconciliation contributes to structuring the debate. It bridges the gap between practitioners and academics, who drive the opposing viewpoints. This paper's contribution guides future research in deriving and testing more empirically valid constructs regarding people analytics. Its argumentation is based on an exhaustive review of academics' and practitioners' literature. The remainder of the manuscript is organized as follows: section two introduces the core ideas behind people analytics, section three depicts the literature search and coding approach, and lastly, section four presents the findings and discusses the implications.

2 Background: Datafication of Human Resources

In the 21st century, discussions around big data and data-driven activities spawn in any business function. For people analytics, the nucleus is found in the human resources function, which progresses from basic controlling metrics and key performance indicators. It sees prospects in collecting and analyzing data about employees' behaviors to transform their decision-making from intuitive and experiential toward data-driven and evidence-based for informing traditional human resources processes (Marler & Boudreau, 2017). Although people analytics originated in human resources, the topic is relevant for any business function concerned with people management (Fecheyr-Lippens et al., 2015). The underlying premise is that data is objective and leads to better decisions than intuition, ultimately guiding organizations to achieve higher performance.

Predictive modeling that generates insights from descriptive and inferential statistical techniques is involved in people analytics. Information technology artifacts play a focal role. Compared to traditional human resource information systems (Dulebohn & Johnson, 2013; Ives et al., 1980), people analytics bears novel features that bring about altered organizational implications. So far, these implications are poorly understood because the underlying mental conceptions of people analytics vary considerably (Hüllmann & Mattern, 2020; Tursunbayeva et al., 2018). For example, Marler and Boudreau (2017, p. 15) define people analytics as a digital "human resources practice", whereas Cheng (2017, p. 2) understands it as a type of software tool. In contrast to this operational level of activity, Lawler and Boudreau (2015) consider people analytics a strategic approach with the means for strategic influence and guidance, delivering competitive advantage.

2.1 The Debate: Critics' and Proponents' Opposing Viewpoints

The variety in goals, analytical methods, and data sources is conducive to the contentious debate and controversy. Critics focus on people analytics as an exclusively quantitative approach using algorithms for analyzing big data, behavioral

data, and digital traces. This conception causes criticism because it entails collecting employees' behavioral data at a fine-granular level.
Big data is not neutral. The algorithms reproduce the bias and discrimination inherited from the historical data, as well as the design choices by the developers (Gal et al., 2020; Hüllmann et al., 2021; Tursunbayeva et al., 2021). For example, the Amazon hiring algorithm got scrapped because it discriminated against females (Dastin, 2018). The reduction of complex social phenomena to simple metrics can give a false sense of objectivity (Gal et al., 2017). Construct validity of instruments based on behavioral data should be ensured through independent scientific studies (Braun & Kuljanin, 2015). However, the algorithms are often proprietary and opaque. Thus, validity cannot be guaranteed, and affected employees are unable to evaluate the algorithm (Goad & Gal, 2018). At the same time, more transparency increases the risk of "gaming the metrics", further questioning the algorithms' validity (Hüllmann, 2019). Reducing people-related organizational outcomes to mere performance metrics that can be optimized disregards the humans' feelings, intentions, and context, leading to dehumanization of work (Riemer & Peter, 2020). Similarly, optimization through nudging and shaping human behaviors can be considered manipulation (Tursunbayeva et al., 2021). All these issues can result in discomfort and stress for the employees, counteracting any positive effects. Tursunbayeva et al. (2021) report that the collection of behavioral data may extend into the employees' personal lives, escalating the looming issues surrounding privacy invasion, surveillance, ethics and legal risks (Hüllmann et al., 2021).

Despite these issues, around 70% of large enterprises consider people analytics a high priority and report having a people analytics team (Hüllmann & Mattern, 2020). The proponents of people analytics argue that it is not exclusively about algorithms and AI-based automation of human resources tasks. It is not about surveilling individuals. Instead, they argue that people analytics is about the scientific approach of hypothetic-deductive inquiry and reasoning, that is, evidence-based optimization of people-related processes. It is about hypothesis testing and rigorous analyses on the team- and organizational-level based on high-level aggregated and anonymized behavioral data (Angrave et al., 2016; Huselid, 2018). Bias and discrimination are avoided by using empirically validated instruments (Huselid, 2018) or conducting qualitative research that does not suffer from statistical errors (Levenson, 2018; Simón & Ferreiro, 2018). This understanding of *aggregate* employee behavior implies that people analytics supports enhancing job performance through changes in work design and organizational staffing (Levenson, 2018). It can help to scrutinize informal structures and relationships for improving engagement (Leonardi & Contractor, 2018), or alter human resources processes such as recruiting, training, and staffing, increasing effectiveness and efficiency (Marler & Boudreau, 2017; van den Heuvel & Bondarouk, 2017). Long-term optimization of people-related processes such as workforce planning, talent development, and staffing can achieve strategic competitive advantage (Huselid, 2018; Levenson, 2018).

Clashing norms and values can partially explain this controversy. Clearly, the AI-based tools that automate specific tasks of the human resources function based on an excessive collection of behavioral data do exist (Hüllmann et al., 2021). Practitioners follow commercial interests and deem such approaches viable, whereas critics complain about surveillance and privacy invasion (Hüllmann et al., 2021). Concomitantly, critics may reject people analytics, even if it is based on anonymized and highly-aggregated data on the grounds of dehumanization, little evidence for its positive effects, or risk of reidentification (Marler & Boudreau, 2017). However, the variety in values, norms, and ethics does not explain how high-level aggregated and anonymized data leads to extensive surveillance. It does not explain how interviews and qualitative inquiries can facilitate employee surveillance (Hafermalz, 2021). It does not consider that long-term optimization of human resources processes such as workforce allocation, development, or staffing is different from automating single human resources tasks through behavioral data collection and analysis, such as AI-based video assessments for selecting prospective recruits. These differences in conceptions lead to friction and fuel the controversy and debate. For the debate to be more productive, it needs to be more nuanced.

3 Methods: Reviewing Academia and Practice

This paper resolves the research question by providing an overview of people analytics, reviewing and organizing academics' and practitioners' literature on the topic. The years from 2014 to 2021 are included since the first hype started around 2014. Based on the results, a multidimensional categorization that captures the dominant variants of people analytics' conceptions among practitioners and academics is proposed. To identify relevant pieces of literature, academic databases and consultancy websites were searched by keywords, and additionally, the consultancy websites were searched by manual query. The keywords were selected based on previous studies (Hüllmann & Mattern, 2020; Tursunbayeva et al., 2018). Synonyms such as "HR analytics" and "workforce analytics" were included. The keywords are illustrated in Figure 1 together with the overall search process that resulted in the body of literature of academics' and practitioners' manuscripts.

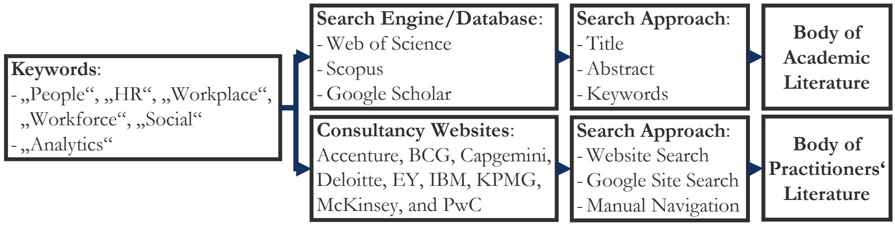

Figure 1: Search Process for Academic and Practitioners' Literature

For searching the academic literature, one search engine and two scientific databases were used to get an exhaustive overview, following established recommendations (vom Brocke et al., 2009; Webster & Watson, 2002). For querying the databases, the fields *title*, *abstract*, and *keywords* were used to balance precision and recall. The search query was constructed by concatenating each keyword with "Analytics" (Figure 1) and joining the concatenations by the "OR" operator. The "OR" operator was also used to account for common synonyms (e.g., "HR" OR "human resource[s]"). Because Google Scholar does not index the abstract or keywords, the results were filtered through the title field using advanced search and the parameter "allintitle:". To reduce the number of consultancies, the top 20 consultancies by revenue were identified (Gartner, 2018), expecting relevant input in terms of research and development on a novel topic such as people analytics. Preliminary screening to determine if the consultancies provide relevant input, services, or expertise on people analytics yielded the nine consultancies shown in Figure 1 (ordered alphabetically). To identify relevant information on the consultancies' websites, three different search approaches based on the keywords were applied (cf. Figure 1): **(1)** Use of the search function of the website; **(2)** Use of Google's site search function (e.g., site: http://example.com/ "HR "analytics"); **(3)** Manual navigation through the website.

Most consultancy websites do not have a search function, and Google search provides too many irrelevant results (similar to Google Scholar). Thus, the websites were manually navigated and scrutinized for relevant information based on the keywords. The search was conducted by the author and two research assistants. Since each consultancy named and positioned the relevant sections of their website differently, following hyperlinks was ad-hoc and based on intuition.

Table 1: Coding Scheme adapted from Hüllmann and Mattern (2020)

Dimension	Explanation
Information Technology	What is the role of information technology?
Data Sources	What data sources are collected and analyzed?
Methods	What are the methods being used?
Stakeholders	Who is responsible and drives the topic?
Scope	What is the scope of outcomes, goals, or purposes?
Unit of Analysis	Which unit of analysis is depicted?
Consequences	What are the consequences of applying people analytics?

The information gathered from the literature is analyzed using a coding scheme developed by Hüllmann & Mattern (2020), rooted in early information systems frameworks (Ives et al., 1980). The coding scheme breaks down the implicit assumptions and mental representations into smaller constituents, enabling demarcation of people analytics' conceptions in detail. From the coding scheme, the dimensions relevant to answering this paper's research question were selected (Table 1). The analysis is conducted through an explorative two-cycle coding approach (Saldana, 2009). During the first cycle, the author and two research assistants independently generated codes from the manuscripts, inductively, yielding a diverging set of codes. The codes differed in syntax (the words being used as the codes) and semantics (what was meant by the codes). During the second cycle, the same researchers jointly resolved all non-matching codes to agree on the final set of codes, from which the results are derived.

4 Findings: Operational versus Strategic People Analytics

The literature search yielded more than 100 papers after querying the databases by title, abstract, and keywords. After inspecting the full text and screening for relevance to the research question, 42 papers were included in the analysis. The results show that there is unanimity in the fact that people analytics is a tool for supporting decision-making related to people outcomes in the organization. In the details, however, two overarching people analytics' conceptions based on the targeted level of managerial activity were identified (Anthony, 1965): **strategic** and **operational people analytics**. All dimensions were coded for practitioners and academics each, extracting and condensing the findings, which are summarized in Table 2. Operational people analytics emphasizes the digitalization of operational human resources processes through machine learning and information technology. It is perceived as the next incremental step to digitize human resources processes and practices by applying quantitative, data-driven methods. It focuses on human resources functions' core objectives, such as hiring, retention, staffing, and uses quantitative and data-driven approaches. Both academics and software vendors leverage this conception by focusing on tools that support or automate single human resources processes or tasks, for example, AI-based video assessments. Strategic people analytics turns away from perceiving people analytics as an operations supporting tool and advertises the "next evolution step for the human resources" function instead. It focuses on leveraging people analytics for strategic processes such as long-term workforce development and the firm's digital transformation. The main areas of application are workforce, talent, and leadership development and the strategic alignment of the human resources strategy with the overall business strategy. It subsumes qualitative and quantitative approaches. The insights are used for manual and semi-automated analyses to inform strategic planning processes. Following this conception, people analytics is not only a topic for middle management and human resources executives but branches out to the broader senior and c-level. Consultancies drive this conception, advertising high-level consultancy services and promising a strategic role for the human resources function.

Compared to traditional human resource information systems, both the operational and strategic people analytics' conceptions share novel characteristics in (1) unprecedented availability of data (big data), (2) the data's behavioral nature providing fine-grained insights, (3) advanced computational capabilities to perform complex AI-based calculations.

Table 2: Multidimensional Categorization of People Analytics (HRIS = human resources information systems; *interviews includes expert panels, workshops, observations, focus groups; **workshops includes SWOT-analysis, balanced scorecards)

Dimension	Characteristic	Sources (Academic; *Practitioners*)
Scope	Core objectives in HR Function	(Baesens et al., 2017; Tursunbayeva et al., 2018; van den Heuvel & Bondarouk, 2017); (Fineman, 2016; Guenole et al., 2018)
	Long-term workforce planning	(Angrave et al., 2016; Marler & Boudreau, 2017; McIver et al., 2018); (Bachman et al., 2015; Fineman, 2016)
	Digital transformation	(Angrave et al., 2016; Simón & Ferreiro, 2018); (Fecheyr-Lippens et al., 2015; Silvestre et al., 2015)
Unit of Analysis	Individual	(van den Heuvel & Bondarouk, 2017); (Collins et al., 2017)
	Group/Organization	(Levenson, 2018); (Bachman et al., 2015; Fineman, 2016)
Data Structure	Structured	(Baesens et al., 2017); (Fern et al., 2014)
	Unstructured	(Angrave et al., 2016; McIver et al., 2018)
Data Sources	Digital Traces	(Hüllmann & Kroll, 2018; McIver et al., 2018); (Sweeney et al., 2016)
	Sensors	(Hüllmann et al., 2021); (Arellano et al., 2017)
	(Pulse) Surveys	(Angrave et al., 2016; Levenson, 2018); (Guenole & Feinzig, 2016)
	Interviews*	(Levenson, 2018); (Silvestre et al., 2015)
	HRIS	(Levenson, 2018); (Guenole & Feinzig, 2016)
	Video/Audio	(Hüllmann et al., 2021); (Collins et al., 2017)
	External Data Sets	(Baesens et al., 2017); (Fern et al., 2014)
Data Content	Personnel Data	(Baesens et al., 2017);
	Project Data	(Baesens et al., 2017; Levenson, 2018)
	Psychometric Data	(Arellano et al., 2017)
	Location	(Baesens et al., 2017; Simón & Ferreiro, 2018)
	Behavioral	(Kremer-Davidson et al., 2016); (Fineman & Solow, 2018)
	Market Data	(Marler & Boudreau, 2017); (Fern et al., 2014)
Quantitative Methods	Clustering	(Simón & Ferreiro, 2018); (Arellano et al., 2017; Fecheyr-Lippens et al., 2015; Fern et al., 2014; Guenole et al., 2018)
	Network Analysis	(Levenson, 2018); (Fern et al., 2014; Guenole et al., 2018)
	Null Hypothesis Significance Testing	(Simón & Ferreiro, 2018; van den Heuvel & Bondarouk, 2017); (Fern et al., 2014; Guenole & Feinzig, 2016)

	Machine Learning (Video, Audio, Text)	(Angrave et al., 2016; McIver et al., 2018; Shami et al., 2015); (Fecheyr-Lippens et al., 2015; Silvestre et al., 2015)
Qualitative Methods	Interview Coding, Workshops**	(Kremer-Davidson et al., 2016; Levenson, 2018); (Fecheyr-Lippens et al., 2015)
Consequences	Ethics & Legal	(Gal et al., 2017); (Guenole et al., 2017)
	Surveillance	(Hüllmann et al., 2021); (Guenole et al., 2017; Schwieters, 2015)
	Wellbeing & Stress	(Tursunbayeva et al., 2021); (Guenole & Feinzig, 2016)
	Statistical Issues validity, bias, discrimination	(Gal et al., 2020; Hüllmann & Mattern, 2020); (Guenole & Feinzig, 2016)
	Implementation change management, skillgap	(Hüllmann & Mattern, 2020); (Bachman et al., 2015; Guenole et al., 2017)

The differences between the identified people analytics' conceptions and traditional human resources information systems exacerbate the contentious debate. People analytics' novel characteristics cause negative consequences. Combining the novel extent of available data with the data's behavioral nature allows fine-granular tracing of employee behavior, depicted as the metaphorical panopticon (Hafermalz, 2021). Through extensively monitoring employee behavior, the panopticon inhibits the behavioral mechanisms theorized by Altman (1977) for reaching an individual's desired privacy outcomes. Conversely, fine-grained monitoring enables more precise decision models for personnel decisions, improving the effectiveness of human resource information systems on the operational level. Simultaneously, more data and advances in artificial intelligence technology enable decision support for less structured decision problems, that is, problems on the strategic level of managerial activity. Strategic people analytics with qualitative approaches or highly aggregated and anonymized data sources, however, is unproblematic in terms of surveillance—except for risks of reidentification or dehumanization.

This paper advances the understanding of next-generation human resource information systems and their organizational implications. It shows how the differences between operational and strategic people analytics' conceptions explain the controversial debate and the opposing viewpoints. It contributes to bridging the academic and practice divide. Academics' and practitioners' attitudes and purposes differ when talking about people analytics. Academics focus on introducing the topic, presenting state of the art, and providing an outlook for the future. While they highlight the topic's relevance, they emphasize the issues. In contrast, practitioners focus on best practices and advertising people analytics products as the next evolution of human resources, emphasizing benefits and opportunities. The academic literature takes a more neutral perspective and tries to make sense of the practices associated with people analytics, whereas practitioners are more hands-on and pursue commercial interests. Summarizing the results, this paper contributes four tentative propositions based on people analytics' novel characteristics and the two overarching conceptions:

Operational Level People Analytics: (1) A large amount of behavioral data and computational advances (machine learning/AI) enable fine-grained insights for broader automation of structured personnel decision problems compared to traditional human resource information systems. **(2)** Operational people analytics, driven by academics and vendors, suffers from privacy concerns as individuals are monitored through large-scale behavioral tracking and quantitative analyses (=AI tools), which inhibit privacy regulation behaviors.

Strategic Level People Analytics: (3) A large amount of behavioral data and computational advances (machine learning/AI) enable more effective human resource information systems for less structured decision problems compared to traditional human resource information systems. **(4)** Strategic people analytics, driven by consultancies, does not suffer from privacy concerns (that much) as the relevance of daily fine-grained monitoring is reduced over aggregated data and qualitative approaches (=consulting practice).

5 Limitations and Conclusion: Moving People Analytics Forward

This paper's limitations include that only literature until 2021 was analyzed, although people analytics is a dynamic topic and changes occur quickly. Only a selection of large consultancies was considered, so generalizability to small and medium consultancies might be limited. The filtering was subjective, and other researchers might include different papers. Differentiating the conceptions based on a single dimension does not work because the same data sources or analytical methods can be used for both operational and strategic improvements, as methods such as machine learning are generic. Thus, it is crucial to consider the combination of scope, analytical methods, and data sources that make up a conception. Due to space limitations, not all conceptual details could be fused out. Instead, the multidimensional categorization and the two conceptions are briefly depicted before outlining the theoretical propositions. So far, the results remain conceptual, and empirical evidence for the propositions is lacking. The next steps are adjusting the multidimensional categorization according to peer feedback and validating the suggested propositions with an online experiment (Schulz et al., 2010). Concluding, this paper contributes four propositions that advance the theory of people analytics. The gap between academia and practice is highlighted. Managers are encouraged to consider the academic discourse on people analytics and be aware of the different conceptions. These different conceptions have divergent implications that must be addressed when implementing people analytics.

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Appendix

The literature review followed recommendations by Jan vom Brocke et al. (2009). Google Scholar was used to add manuscripts that might be missing from Scopus or Web of Science. Unfortunately, the exact numbers were not documented for Google Scholar. The consultancies were selected so that relevant input for the research question is available.

Search Results for Academic Papers				
	Web of Science	Scopus	Google Scholar	Total
People Analytics	49	67	(n/a)	
Workforce Analytics	35	53	(n/a)	
Workplace Analytics	1	3	(n/a)	
Human Resources/HR Analytics	63	98	(n/a)	
Social Analytics	58	99	(n/a)	
Total	206	320	(n/a)	
Total after removing duplicates	188	304	(n/a)	
Total after merging				**280**

Search Results for Consultancies Papers	
Deloitte	14
Capgemini	3
Accenture	13
PwC	11
KPMG	5
McKinsey	7
EY	1
BCG	3
IBM	8
Total	**65**

Filter	**Academic Papers**	**Consultancies Papers**	**Total**
After search	280	65	
After screening abstract	60	(n/a)	
After screening fulltext	28	14	
Total papers included in analysis			**42**