When Technology Becomes an Ideological Battleground: How Data Ideology affects Affordance Actualization in People Analytics

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Abstract: Datafication technologies increasingly impact today's workplaces, as employees' behavioral data are collected and analyzed for organizational purposes. While datafication technologies can increase organizational efficiency, they come with the risk of employee surveillance and discrimination. As a result, their implementation is surrounded by controversy. Understanding the different perceptions and assumptions about these technologies from individuals with diverse functional roles is crucial to successfully implementing datafication technologies. Based on 43 interviews, we first investigated how individuals with different functional roles evaluate people analytics, as a manifestation of datafication technologies, using the well-known lens of affordances. Inconclusive results led us to explore further and investigate whether and how perceptions of datafication technologies, as well as affordance actualization, can be explained by data ideologies. Our findings from a critical realist analysis offer novel theoretical and empirical insights into the concept of data ideologies. Data ideologies offer a useful extension to the affordance theory and help explain the relationship between varied stakeholders and datafication technologies along three mechanisms: moderation, confirmation, and modulation. The theorized mechanisms have implications for deploying datafication technologies in practice.

Keywords: Datafication technology, people analytics, affordances, data ideology, qualitative study, critical realism, generative mechanisms

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Abstract

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1 Introduction

The trend to datafication at the workplace surges, fueled by more remote work during the pandemic and a rapid proliferation of novel datafication technology (Mettler, 2023). This trajectory is accompanied by shifts in cultural values that deem datafication at the workplace acceptable (Hüllmann, 2022; Ngwenyama et al., 2023). Datafication describes the process of collecting, analyzing, and acting upon employees' behavioral data and is enabled by the growing digitization of organizational activities (Schafheitle et al., 2020). Datafication technologies are information systems (IS) that facilitate such datafication processes.

One group of datafication technologies is people analytics (PA), which is geared towards the human resources (HR) function and employee management. PA describes IS that "analyze [people] data […] for patterns and present decision-makers with more granular views of organizational resources, processes, people, and their performance" (Gal et al., 2020, p. 1). These technologies can support diverse tasks in the HR function, such as hiring, retention, onboarding, performance measurement, or employee training (Hüllmann et al., 2021). PA is a representative manifestation of datafication at the workplace due to the sensitivity of employee data collected, the high degree of uncertainty and algorithmic opacity, and the controversy between different user groups (McCartney & Fu, 2022). Prior literature often addresses different perceptions and uses of technologies by individuals via the concept of affordances (Werkhoven, 2017). Following the definition of affordances as "the potential for behaviors associated with achieving an immediate concrete outcome and arising from the relation between an artifact and a goal-oriented actor or actors" (Strong et al. 2014, p.12), the different positions on PA might originate from the fact that individuals with different goals interact with the technology. In existing literature, individual differences in affordances are theorized to arise either from different goals (e.g., related to functional role) or different potencies (e.g., the required effort or skill) to actualize an affordance (Anderson & Robey, 2017). Subsequently, it is often assumed in extant research that if the potential actions associated with a technology are in line with an individual's goals, and if the individual has the necessary energy and skill to interact with the technology or a supportive context to acquire them, then affordances will be actualized (Anderson & Robey, 2017)

We challenge this taken-for-granted assumption and suggest that individual differences in affordances, their potency, and their actualization can also arise from different normative values – in our case, values about data. Following recent studies, we see perceptions of technical objects as linked to personal values (Lichti & Tumasjan, 2023). Datafication technologies such as PA are often implicitly associated with dataism. Dataism is an ideology or a set of beliefs that assumes all kinds of human behavior can be quantified (Harari, 2017; Mari & Petri, 2022). However, organizations are filled with not just data enthusiasts but also data agnostics, ambivalents, and critics – all of whom engage with datafication technologies, such as PA, to some extent. Therefore, recognizing different data ideologies and the corresponding engagement with datafication technologies is crucial if we are to understand and guide the messy, tension-filled reality (rather than wishful visions) of implementing and adopting datafication technologies in organizations. To this end, data ideologies might explain the interindividual differences beyond goals, skills, and potency, and why individuals reject datafication technologies such as PA despite having matching goals, skills and potency (or vice versa and accept them).

To the best of our knowledge, prior insights on the role of ideologies in actualizing affordances are limited. Likewise, research on the different affordances of datafication technologies such as PA is only emerging with limited empirical insights so far (McCartney & Fu, 2022). We therefore pose the research question (RQ): *How does an individual's data ideology affect the actualization process of datafication technology affordances?*

The paper is structured as follows to address the research question: First, the concepts of datafication technologies and specifically PA are introduced, followed by the theoretical lens of affordances and an introduction of data ideologies. Then, we describe the method and data collection. We address the research questions by a qualitative, critical realist study. We interviewed 43 PA practitioners about the affordances they perceive in PA. By understanding which assumptions about data are behind their perceptions, we can disentangle the underlying sets of beliefs regarding datafication technologies. We reflect on these insights in the discussion, highlight the scientific contributions and implications for practice, and point out limitations and future research directions.

We contribute to the literature on datafication and PA in multiple ways. To the best of our knowledge, this study is one of the first empirical investigations on PA, complementing the various conceptual pieces (Gal et al., 2020; Giermindl et al., 2022). We describe specific affordances perceived by individuals with different functional roles. We contribute to the datafication discourse by showing how datafication both co-occurs with and diverges from the dataist ideology, offering a novel and nuanced explanation of the mixed receptions that datafication technologies have in organizations. We further contribute to understanding the actualization of affordances. Extending the concepts of affordances and their potency with data ideologies, we contribute to affordance theory, which has recently been criticized as stagnant (Leonardi, 2023), and deepen the theoretical lens for further application. Specifically, our findings suggest that ideologies (such as about data) may better explain the (non-)actualization of affordances beyond established concepts such as affordance potency, user goals, and user skills. The implications include recommendations for managers initiating PA projects and PA vendors developing PA solutions.

2 Related Work

2.1 People Analytics as an Instance of Datafication Technologies at the Workplace

Datafication describes a trend on the societal and organizational level towards adopting the process of transforming "reality" into "computerized, quantitative data to generate new forms of value" (Schafheitle et al., 2020, p. 456). This trend relies on ubiquitous computing and the digitization of everyday work life. As employees become "walking data generators" (McAfee & Brynjolfsson, 2012, p. 5), their work behaviors are tracked in the form of digital traces and made observable (Aaltonen &

Stelmaszak, 2023; Hüllmann, 2022). Based on the fine-grained information about employee behaviors, datafication technologies are used for management and control (Benlian et al., 2022; Möhlmann et al., 2021; Polzer, 2022).

One instance of a datafication technology is PA. It is an umbrella term that subsumes "human resources analytics", "workforce analytics", and "workplace analytics" (Tursunbayeva et al., 2018). PA is an appealing manifestation of datafication technologies to explore because it highlights four distinct characteristics of datafication: (1) The behavioral employee data collected and analyzed are sensitive, and (2) decisions based on these data, like hiring or firing, are 'existential' for employees (McCartney & Fu, 2022). (3) Decision support through PA is paired with high uncertainty and black-boxed mechanisms of how algorithms come up with recommendations (Gal et al., 2020) which is why (4) PA sparks controversial debate among individuals with different functional roles (Hüllmann, 2022).

In academia, the risks and benefits of PA have been predominantly discussed conceptually. On the one hand, PA is argued to increase process efficiency (Mirbabaie et al., 2021), optimize employee allocation, support different HR functions, and improve decision-making (Tursunbayeva et al., 2018). PA can empower employees and managers (Gierlich-Joas et al., 2024), help in negotiating workloads (Nyman et al., 2023), and lead to a redefined identity in the HR function (Gierlich-Joas & Zimmer, 2023). Further works provide an overview of why and how datafication technologies such as PA should be used on different levels of managerial activity (e.g., Ellmer & Reichel, 2021; Huselid, 2018; Leonardi & Contractor, 2018). On the other hand, datafication technologies are suggested to lead to a "totalitarian surveillance state" (Wiener et al., 2019, p. 1396). With increasing amounts of data becoming accessible, PA facilitates surveillance (Mettler, 2023) and increases employee privacy threats (Klöpper & Köhne, 2023). This type of data-driven management can negatively influence well-being in the workplace (Wang et al., 2020). For example, excessive transparency can stress employees (Tams et al., 2020). PA is also criticized for incorporating biases and carrying ethical concerns due to the underlying mechanisms' opacity (Giermindl et al., 2022).

2.2 Affordances Lens to Analyze People Analytics' Use

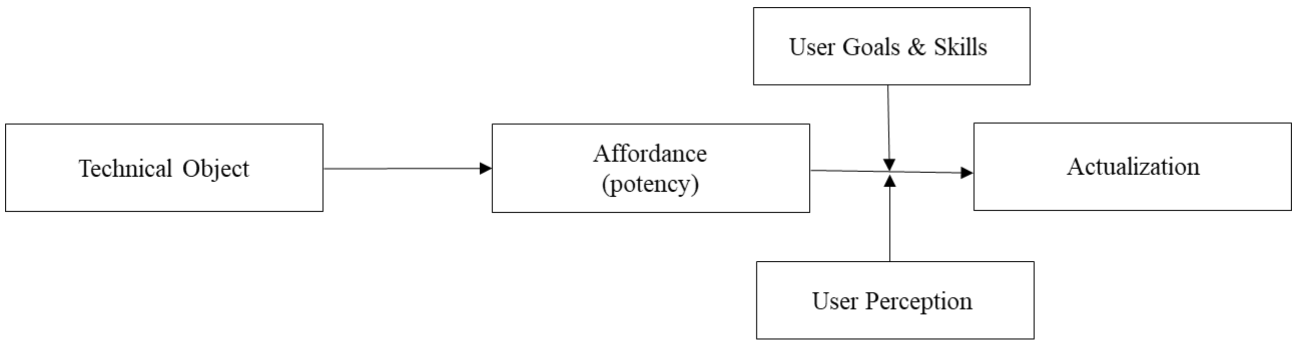
Originating from Gibson (1977) who describes goal-oriented actors' interpretation of how an object in an environment can be used, affordance theory has been adapted to the IS context. It is used to analyze the features of technical objects and how humans interpret them, which is a phenomenon at the core of the discipline (e.g., Leonardi, 2023; Orlikowski, 2000). Building on the original Adaptive Structuration Theory (AST) by DeSanctis & Poole (1994), Markus & Silver (2008) introduce functional affordances as a concept to describe the interactions between a technological object and humans. The technical object refers to the IT artifact itself, which is material and does not depend on individuals' perceptions. This concept is similar to what DeSanctis and Poole define as 'structural features' and does not contain information on the use of the IT artifact (DeSanctis & Poole, 1994). In contrast, functional affordances are a relational concept that refers to the technical object's interaction with different user groups (Markus & Silver, 2008). Functional affordances are defined as "the possibilities for goal-oriented action afforded to specified user groups by technical objects" (Markus & Silver, 2008, p. 622). Markus and Silver (2008) highlight the non-deterministic action potential for users to apply the technical object and focus on the situation- and individual-specific appropriation of technical features (Grgecic et al., 2015)—in other words, how users make the technology their own. This underlines the socio-technical nature of affordances that arise from the relation between a user and a technical object and not from the technical object per se (Volkoff & Strong, 2017)

From these early works, IS researchers have developed affordance theory further, for example, by adding new definitions, such as affordance as "the potential for behaviors associated with achieving an immediate concrete outcome and arising from the relation between an artifact and a goal-oriented actor or actors" (Strong et al., 2014, p. 12). Such additions enhance the theory's fit for analyzing the use of technical objects in organizational contexts (Volkoff & Strong, 2017). Sub-concepts have been introduced, for example, Leonardi's conceptualization of shared and collective affordances (Leonardi, 2013) as well as reflections on the interplay between agency and affordances (Leonardi, 2023). The underlying ontology has been discussed critically (see Appendix for further details). Some scholars subscribe to the understanding of *affordances as property*, which suggests that the affordances of the technical object exist independently of the relationship between technology and humans. Others emphasize the notion of *affordances as cognition*, putting human perceptions in the foreground, and that affordances do not exist independently of perception (Leonardi, 2023). Further discussions on the underlying philosophical foundations for affordance research have arisen, building on agential realism or critical realism (Leonardi, 2023; see Appendix for further details). Most studies, including ours, take a critical realist stance, which is in line with *affordances as property*, and postulate that affordances exist even though the actor may not perceive them (Volkoff & Strong, 2013).

According to critical realism and *affordance as property*, technology can have properties that "predate the actions to which it will be put and the perceptions it will help create" (Leonardi, 2013, p. 69). This logic is essential for analyzing the perceptions of datafication technologies, especially as not all people may have used them, yet form opinions about them. At the same time, this notion maintains that affordances are a relational concept, describing the potential individual-specific appropriation of technology. The individual perception and appropriation are shaped by people's goals and skills and can change over time (Leonardi, 2013; Markus & Silver, 2008). Critical realism as a philosophical stance has several benefits for affordance research such as straightforward application to empirical data and avoiding ontological problems with the exclusively co-constitutive relationships (i.e., things can exist without each other) (e.g., Bygstad et al., 2016; Lehrer et al., 2023; Leidner et al., 2018). Finally, this understanding of affordances allows us to "examine how people come to understand, interpret and deal with the materiality that *pre-exists their interaction* with technology" (Leonardi, 2013, p. 71, *emphasis added*).

Following a critical realist stance and the definition by Strong et al. (2014), we study affordances of datafication technologies that may pre-exist prior to any actual interaction with the technology. Thus, in order to create a concrete outcome, an affordance needs to be actualized. We define affordance actualization as "the actions taken by actors as they take advantage of one or more affordances through their use of technology to achieve immediate concrete outcomes in support of organizational goals" (Strong et al., 2014, p. 15). Prerequisites for the actualization of an affordance are whether it is perceived, whether it is in line with the actor's goals, and whether the actor has the skills to actualize it (Strong et al., 2014). However, prior studies reveal that even when all three prerequisites are met, a user may still not actualize an affordance (Anderson & Robey, 2017). An additional factor hampering the actualization of an affordance is the required energy for an individual to actualize it, which is referred to as the potency of an affordance (Anderson & Robey, 2017). If the actualization requires little energy (either mentally or physically), the potency is strong, and the affordance is likely to be actualized. If it requires much energy to actualize an affordance, the potency is weak and users refrain from actualizing the affordance (see Figure 1).

Figure 1. Affordances and their actualization (adapted from Anderson & Robey, 2017)



We follow this line of thought, introducing the possibility of normative values about a technical object playing a significant role in the actualization of affordances. Even if all prerequisites to actualize an affordance are met, an individual may find it too mentally onerous to actualize an affordance given their personal value-laden judgment of the technology. Values have, until now, played a surprisingly small role in theorizations of new technology appropriation, which have heavily favored discussions of different goals and work environments (Anderson & Robey, 2017; Strong et al., 2014). With some emerging technologies, this ignorance of values may not be an obstacle to comprehending their implementation and outcomes. However, with datafication technologies such as PA – involving sensitive data, high-stakes decisions, and opaque technical objects – value-laden judgments (with or without a factual basis) are an essential element of any plausible explanation of PA implementation and use outcomes (Cheikh-Ammar, 2018; Lichti & Tumasjan, 2023). Since the theoretical lens of affordances does not explicitly model how value-laden judgments are formed and how they may shape affordances and their actualization, we turn to data ideologies as a likely source of value-laden judgments when it comes to datafication technologies per se[2].

2.3 Data Ideologies as a Frame to Judge People Analytics

The concept of ideologies has been used in IS studies to investigate attitudes and involvement, for example, in open-source communities, when functional affordances are insufficient for explanation (Choi et al., 2015; Daniel et al., 2018). An ideology can be defined as "relatively coherently interrelated sets of emotionally charged beliefs, values and norms that bind some people together and help them make sense of their worlds" (Trice & Beyer, 1993, p. 33). Ideologies comprise a shared set of assumptions underlying a group of individuals that guides and legitimizes their behavioral or cognitive processes (Daniel et al., 2018). An individual's "ideology is often integrated with a person's sense of self" (Choi et al., 2015, p. 683). Demarcating individuals or groups by their ideology can thus be used to predict behaviors or beliefs (Ashforth & Kreiner, 1999).

Typically, an ideology's beliefs and values concern economic, social, power, or justice perspectives. The substantive nature of these beliefs and values comprises basic assumptions about reality, which can be normative (i.e., how the world should be) or empirical (i.e., beliefs about cause and effects) (Hartley, 1983). The ideology concept is distinct from the related - and partially overlapping - concepts of subjective norms (Ajzen, 1991) or culture (Leidner & Kayworth, 2006) (see Table A1 in appendix).

When it comes to datafication technologies such as PA, a relevant and well-known ideology to examine is that of "dataism" (or "non-dataism" as its opposite). Crooks and Currie (2021, p. 202) state that appreciating datafication technologies comes with "a concomitant set of beliefs," i.e., an ideology about data that underlies the individual. Data ideology's basic assumptions are not about economics or power per se but emphasize empirical (e.g., can data fully represent a human?) and normative assumptions (e.g., should decisions be based on data only?) about how data represent reality. "In its strongest articulation, this ideology echoes the same claims to objectivity that have

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[2] We recognize that for other types of technologies, the sources of value-laden judgments will likely lie elsewhere.

long haunted statistics: it takes the digital data that describe people, places, and things as proxy for the represented entity" (Crooks & Currie, 2021, p. 203).

The grand assertion of dataism is honoring data as the new objective authority (Jones, 2019; Mari & Petri, 2022), positing a shift in authority from human to data (Harari 2017). Harari (2017) goes as far as "if they have enough data on you, and enough computing power, they know what you feel already and why you feel that way" (p. 37). According to Harari (2017), dataism seeks the "ultimate objectification of reality through mathematical algorithms" (p. 38). People subscribing to dataism, i.e., dataists, share an "unconditional belief in data" (Petri, 2020, p. 32). According to Petri, dataism in its extreme form has five assumptions that characterize a person. A dataist (1) perceives the entire world as a flow of data; (2) believes that data provide a fair and exhaustive representation of reality; (3) has unconditioned confidence in data and bases his/her everyday judgments only on data; (4) believes that artificial intelligence will overcome human intellect; and (5) advocates the concept of cosmic data processing and sees living organisms as biochemical information processing systems.

Antagonists of dataism, who we call "non-dataists," challenge these assumptions (Kelly & Noonan, 2017). For example, Jones (2019) argues that having "all the data" does not render data universal or revolutionary. He substantiates his argument by showing the subjective and error-prone practices of how data come to be and how they are analyzed. Mikalsen and Monteiro (2021) assert that "data is always cooked" (p. 1716) and present findings from a case study that dives deep into how data are accumulated, reframed, and interpreted. According to "non-dataists", data are never neutral or factual since they have been processed many times, and they carry data workers' values and decisions (Parmiggiani et al., 2022). We now set about to breathe life into these ideas about data ideologies and their role in affordances through an empirical investigation of PA.

3 Method

3.1 Research Approach and Philosophical Stance

Our research follows a qualitative, abductive research approach with the underlying philosophy of critical realism (Dubois & Gadde, 2002; Wynn & Williams, 2012). The qualitative approach allows us to investigate a real-life phenomenon in-depth and examine questions on the why and the how (Benbasat et al., 1987).

Critical realism is an ontology put forward by Bhaskar (2008) that describes a pragmatist stance between positivism and constructivism, stating that reality exists independently of our perceptions or knowledge of it. According to critical realism, reality can be stratified into three layers: observable (empirical), actual, and real layer (see Table 1). The *observable* (empirical) layer is what scientists can observe, while the *actual* layer describes the events that happen or do not happen, regardless of whether they are or can be observed. The *real* layer describes the real-world entities and their *causal powers* and *generative mechanisms* that cause the actual events.

Critical realism understands entities as *wholes* composed of *parts* based on a set of relations between the parts. The parts and their relations form the entity. The mechanisms of these relations produce the emergent property of the entity, that is, the entity's *causal power*. Therefore, the mechanisms are also called generative mechanisms.

Table 1. Critical Realism Elements

Layer	Critical realism elements	Realization in this study
Real	Entities	Beliefs, data ideology, affordances, technical object, and human.
	Parts that form the data ideology	Underlying beliefs of data ideology and relations between data-related beliefs that form the data ideology.
	Emergent property	Causal power of data ideology that emerges from the interplay of beliefs.
	Generative mechanisms	Set of causal processes linking data ideology (relations between data-related beliefs) and possible user perceptions and value judgments of PA, affordance potencies, and actualization decisions.
Actual	Events caused by generative mechanisms	(1) the perceived affordance potency (2) value judgments or user perceptions of datafication technology (3) the choice (and enactment) of whether to actualize a datafication technology affordance
Observable / Empirical	Observable outcomes	For example: (1) observable technology use (2) articulated perceptions, beliefs and values

In our study, data ideologies are on the real layer. They are not directly observable, meaning they are not on the empirical layer. Data ideologies' causal power emerges from the relations of data-related beliefs ("the parts that form the whole", Elder-Vass, 2010, p. 69) and the resulting generative mechanisms. Consequently, beliefs are also on the real layer. Other entities are the technical object and the human perceiver and the emerging affordances. Through the outlined generative mechanisms, the beliefs interact with each other to form an emergent property – i.e., the causal power of data ideology – that affects the affordance actualization process (events on the actual layer). The events correspond to each step in the affordance actualization process: (1) the perceived affordance potency, (2) value judgments or user perceptions of datafication technology, and finally (3) the choice (and enactment) whether to actualize a datafication technology affordance (Anderson & Robey, 2017). The events' outcomes can be observed on the empirical layer—for example, observable technology use or articulated perceptions. Notably, single beliefs can be articulated and observable, and thus, exist on the empirical layer (cf. Bhaskar, 2008, p. 2).

It is imperative to uncover the generative mechanisms causing the events and not only look at the observable layer (Bhaskar, 2008). Given limited observability, there may be multiple explanations for events, some more adequate, useful, or truthful than their alternatives. As a result, the critical realism stance is particularly useful for investigating the differential actualization of affordances of datafication technologies because it allows unpacking the interplay between beliefs and how the data ideology's causal power emerges from this interplay. Consequently, it offers highly situated insights explaining different and contradictory observable positions on technologies such as people analytics.

Further, applying a critical realist stance goes hand in hand with abductive theorizing (e.g., Mueller & Urbach, 2017; Wynn & Williams, 2012). Abduction is positioned in between deduction and induction, implying that one generates insights "based both on real-world observations that are inductively observed as well as theoretical viewpoints, premises, and conceptual patterns that are deductively inferred" (Gregory & Muntermann, 2011, p. 7). It means starting to analyze incomplete observations using the most feasible explanation of the phenomenon (Dubois & Gadde, 2002; Mueller & Urbach, 2017). However, abduction allows for multiple ways to explain an observation. Thus, during the process of analyzing and explaining the phenomenon, more suitable explanations may replace the initial ones (Mueller & Urbach, 2017)

3.2 Two-staged Data Collection in 2018 and 2021 with People Analytics Experts

Our data collection comprised two stages. We collected data from German companies in two periods (2018 and 2021) to account for the development of the PA artifacts and their use. In the first step, we identified potential interview partners via PA market reviews and LinkedIn searches. We chose maximum variation expert interviews over case studies to unpack the phenomenon from distinct perspectives, with interdependent user groups, and across multiple industries (Patton, 2002). When approaching potential interviewees, we applied the following sampling criteria to ensure the validity of our study: 1) interviewees should either hold a higher management position or be members of PA teams, 2) they should work in Germany, and 3) they should have different levels of experience to include novices and experts on the PA.

The first sampling criterion guaranteed that the interviewees would qualify as experts by either holding a managerial position to drive a PA implementation or being a subject matter expert in the field. Interviewing individuals with different functional roles allowed us to shed light on the different affordances and affordance potency of these individuals. Second, we consciously sampled experts in Germany only, as the implementation of PA is strongly impacted by legal regulations, which are relatively strict in this country. Limiting the data collection to Germany ensured the interviewees were exposed to similar cultures at their workplace, which might also impact their perception of PA. The third sampling criterion provided the opportunity to uncover affordances, their potency, and data ideologies before and after interacting with PA. Hence, we sampled experts at different stages of the implementation, from initiation to adoption, adaptation, acceptance, routinization, and infusion (Table 2). Some of them had already actualized affordances, whereas others were mainly providing insights into their perceptions and goals. Besides the (future) users of PA, we extended the range of interview participants to four vendors of PA. The vendors shared their intentions and underlying beliefs when crafting the technology.

Table 2. Overview of the Interview Partners (M=Manager, E=Employee, V=Vendor)

ID	Position	Industry	Company size	Usage of PA	Stage of PA implementation	Time of interview
1	CHRO (M)	Utilities	1500	n.a.	Initiation	July 2018
2	CEO (M)	Logistics	500	n.a.	Initiation	July 2018
3	CHRO (M)	Manufacturing	5500	n.a.	Initiation	July 2018
4	Senior Manager (M)	Auditing & Consulting	200,000	n.a.	Initiation	Aug 2018
5	CHRO (M)	Media	15,000	n.a.	Initiation	July 2018
6	CEO (M)	IT Consulting	150	MS Power-BI	Adoption	July 2018
7	Lead People Development (E)	Media	15,000	n.a.	Initiation	July 2018
8	Head of Marketing (E)	IT Consulting	150	n.a.	Initiation	July 2018
9	Head Profes. Service (E)	IT Consulting	150	n.a.	Initiation	July 2018
10	Business Unit (E)	IT Consulting	150	BI Tool	Adoption	Aug 2018
11	Business Unit (E)	IT Consulting	5000	n.a.	Initiation	July 2018
12	Branch Manager (E)	Telecomm.	200	n.a.	Initiation	July 2018
13	HR Officer (M)	Logistics	200	n.a.	Initiation	July 2018
14	Partner (M)	IT Consulting	150	BI Tool	Adoption	Aug 2018
15	CEO (M)	IT Services	300	n.a.	Initiation	July 2018
16	Team Lead HR (M)	Software	1000	Hiring, Onboarding	Adoption	June 2021
17	Team Member PA (E)	Software	1000	Hiring, Onboarding	Adoption	July 2021
18	Team Lead PA (M)	E-Commerce	500	Hiring, Performance Assessment, Talent Mgmt.	Acceptance	July 2021
19	Team Member PA (E)	Media	1500	Workforce Planning, Performance Assessment	Acceptance	June 2021
20	Team Lead HR (M)	Finance	500	Workforce Planning, Hiring	Acceptance	June 2021
21	Team Member PA (E)	Finance	1500	Workforce Planning, Churn Management	Routinization	June 2021
22	Team Member PA (E)	Manufacturing	1500	Workforce Planning, Churn Management	Routinization	June 2021
23	PA Consultant (E)	Consulting	500	All fields	All levels	July 2021
24	PA Consultant (E)	Consulting	100	All fields	All levels	July 2021
25	Employee R&D (V)	Software	50	Hiring, Onboarding	Routinization	June 2021
26	CEO (V)	Software	50	Workforce Planning, Churn Management	Routinization	July 2021
27	CEO (V)	Software	10	Workforce Planning, Hiring, Talent Mgmt.	Routinization	July 2021
28	Co-CEO (V)	Software	10	Predictive Analytics	Routinization	June 2021
29	Branch Manager (M)	Consulting	200	Descriptive Analytics	Adoption	July 2021
30	Head of HR (M)	Consulting	200	Descriptive Analytics	Adoption	July 2021
31	Branch Manager (M)	Consulting	200	Descriptive Analytics	Adoption	July 2021
32	Consultant (E)	Consulting	200	Descriptive Analytics	Adoption	July 2021
33	Consultant (E)	Consulting	200	Descriptive Analytics	Adoption	July 2021
34	Team Lead (E)	Services	50	Descriptive Analytics	Adoption	July 2021
35	Head of HR (M)	Services	50	Descriptive Analytics	Adoption	Aug 2021
36	Team Lead (E)	Services	50	Descriptive Analytics	Adoption	Sep 2021
37	Head of HR (M)	Retail	400	Descriptive, Predictive	Adoption	July 2021
38	Employee HR (E)	Retail	400	Descriptive, Predictive	Adaption	Aug 2021
39	Head of HR (M)	Manufacturing	400	Employee Surveys	Acceptance	Aug 2021
40	Head of HR (M)	Manufacturing	400	Employee Surveys	Acceptance	Sep 2021
41	Head of HR (M)	Health	150	Descriptive Analytics	Acceptance	Aug 2021
42	Head of Area (E)	Health	150	Descriptive Analytics	Acceptance	Sep 2021
43	CEO (M)	IT Consulting	150	BI Tool	Adoption	Aug 2018

The interviews were the building blocks of our data collection. They covered the topics of introduction, company setting, understanding of PA, use of PA, and perceived risks and benefits of PA. We posed questions like “What is your current usage of people analytics inside your company?”, “Why are you (not) using people analytics?”, “How has the use of people analytics affected your work (as a manager / employee)?”, and “What benefits / risks do you see with people analytics?”. The questions were slightly adjusted to the interviewees’ roles to account for (non-)users, different organizational roles, and vendors’ perspectives relevant to the study. Before conducting the interviews, the research team pre-tested the guideline with two PA experts from the field.

We reached out to the interviewees after identifying suitable candidates according to the sampling criteria. The first data collection, with 15 interviews, took place between July and August 2018. At that time, many German companies were not using PA and had just started evaluating the technology. Building upon these initial insights, we conducted a second round of data collection, consisting of 27 interviews between June and September 2021 with a new set of participants – most of whom had implemented PA. The interviews were conducted in German or English via video conference solutions or the telephone and lasted 30-45 minutes. They were recorded (with the interviewees’ permission), anonymized, and transcribed verbatim (Saldana, 2009). All quotes that we used were translated into English. With 43 interviews (20 with managers, 19 with employees, and 4 with vendors), we reached theoretical saturation such that previously recorded observations were confirmed, and no novel insights were added.

3.3 Data Analysis via Abductive Coding Cycles

Although multiple guidelines for critical realist analyses exist (e.g., Mingers, 2004; Wynn & Williams, 2012), we followed the 6-step framework by Bygstad et al. (2016), because it is established in the IS discipline and is geared towards application together with affordance theory (e.g., Lehrer et al., 2023). The six-step framework consists of the description of events and issues, identification of key entities, theoretical re-description, retroduction (identification of candidate affordances), analysis of the set of affordances and associated mechanisms, and assessment of explanatory power (see 3).

To operationalize the six steps for our abductive coding, we made use of the grounded theory methodology (Corbin & Strauss, 2008; Wiesche et al., 2017). We used the software ATLAS.ti for all coding cycles, and multiple researchers were involved in the coding. To ensure validity, we followed the consensual coding practice (Kuckartz, 2014, p. 74). Throughout numerous meetings and workshops, the coders discussed the results and agreed upon the final codes.

The abductive steps of the critical realist framework included the application of two theoretical lenses: (1) affordances and (2) data ideologies. Since "[our] objective is to discover new things—other variables and other relationships [… and] our main concern is related to the generation of new concepts and development of theoretical models, rather than confirmation of existing theory" (Dubois & Gadde, 2002, p. 559), our abductive approach comprises inductive and deductive coding cycles. On the one hand, we aimed to unpack the affordances of PA as perceived by individuals with different functional roles (see Table 3, steps 1-3). Therefore, the resulting dimensions and themes of this first coding phase are interpreted with the affordance lens. On the other hand, we aimed for an even better-suited explanation to understand people's underlying assumptions about data, motivating a second coding phase. The resulting dimensions and themes are derived from the data ideologies lens (see Table 3, steps 4-5).

Table 3. Overview of Data Analysis (following Bygstad et al., 2016)

Step in the data analysis	Realization in this study
1. Description of events and issues	Open coding for events as clusters of observations made by the researchers related to the introduction of people analytics systems and their material features (technical object)
2. Identification of key entities	Open coding for key entities related to technical and social systems: Perceived outcomes of people analytics systems, that is, the emerging relationship between the technical object and the human perceiver in terms of affordances
3. Theoretical re-description (abduction)	Abductive coding for coding affordance potency, affordance actualization, as well as goals and perceptions based on functional roles
4. Retroduction	Using data ideologies as alternative theoretical lens, first open and then axial coding of data ideologies to identify alternative explanations for the perceptions of people analytics
5. Analysis of the set of affordances and associated mechanisms	Analysis of the generative mechanisms that cause affordance actualization to derive a conceptual model that extends existing theory with the abductively derived dimensions (i.e., data ideologies drive perceptions of people analytics to explain affordance actualization)
6. Assessment of explanatory power	Assessment of why data ideologies are a suitable additional explanation for PA affordance actualization in addition to affordance perception, goal alignment and skills. Discussion of alternative explanations.

In the open coding cycles (steps 1-3 from Table 3), the research team developed a tentative coding scheme (Corbin & Strauss, 1990; Corbin & Strauss, 2008). In the first step, we conducted open coding for events related to the introduction of people analytics systems and the perception of their material features (technical object). Afterward, we identified key entities related to technical and social systems. Specifically, we analyzed the perceived outcomes of people analytics systems, that is, the emerging relationship between the technical object and the human perceiver in terms of affordances. In the third step, we open-coded the affordance potency, affordance actualization, as well as the goals and their perceptions based on the individuals' functional roles.

For these open coding cycles, we focused on breaking down the qualitative data. To this end, we read the transcripts carefully, immersing ourselves in the situated experiences of the interviewees. Following Glaser & Strauss (1967), we went through the data line by line and sentence by sentence to make sense of the necessary nuance. Open coding allows the identification of events and mechanisms from the critical realism layers (see section 3.1). The codes captured the main ideas that each author associated with the respective text fragment. In line with open coding, the codes remained descriptive and close to the actual text. During open coding, we constantly compared the different text fragments to identify commonalities and differences. We not only moved back and forth between different interviewees' transcripts but also between theory and data. Following the abductive approach, we highlighted relevant pieces of the transcript that would illuminate our nascent theoretical intuitions. The codes captured the main ideas that each author associated with the respective text fragment. As new data was analyzed, existing codes were adjusted to more accurately capture the underlying affordances related to the phenomenon of people analytics. Although we were informed by the nascent theory, we made sure that the codes emerged naturally from the transcripts and were not imposed by theory. These steps led to 69 codes around the outcomes and affordances of PA.

While these first steps lead us to a feasible explanation for our empirical observations so far (the affordance lens), we lacked an explanation as to why some affordances of PA are not actualized, even though they were perceived in line with the users' goals, and had a strong potency. We thus set out to revisit the literature in search for alternative explanations. Data ideologies seemed like a promising theoretical lens in addition to the affordance lens.

Throughout open coding, we identified 13 codes for data ideologies representing the individuals' underlying beliefs about data (see Table in Appendix). By aggregating them into categories, we derived codes for the dataist and non-dataist ideologies. With these two data ideologies in mind, we executed the retroduction using axial coding (steps 4 and 5 from 3). We clarified the boundary conditions of the codes and categories across multiple conversations among the authors. By linking affordances and their actualization, we identified the generative mechanisms that underlie the perceptions of people analytics systems. We aggregated everything into a process model by selectively coding and abstracting the categories into higher-level conceptual dimensions. By abductively extending existing theory with those dimensions, we derived the three generative mechanisms and sub-mechanisms of how data ideology affects affordance actualization.

Finally, looking at the findings (step 6 from Table 3), data ideologies and affordances – in combination – offered a better and more plausible explanation for the observable layer than a purely affordance-focused lens. Ideology can help explain why affordances are not always distinguishable by different user groups (Markus & Silver, 2008) and why their actualization is not determined based on whether they are perceived in line with users' goals, and are executable from a user's skills and affordance potency perspective (Anderson & Robey, 2017; Strong et al., 2014). In the discussion section, we elaborate on why the combination of data ideology and affordance theory may offer stronger explanatory power than only affordance theory (Wynn & Williams, 2012).

4 Findings

The six steps of the abductive coding cycles served not only to structure the data but also to present the findings. In section 4.1, we report on steps 1-3 of the data analysis that implied coding for affordances, their potency, their actualization, as well as goals and perceptions grouped by functional roles (see Table 3). We unpack the concept of "perception" not only as binary but as detailed evaluations of PA technology. In section 4.2, we present the findings after the retroduction step (steps 4-5 from Table 3) using the lens of data ideologies, extending the framework by Anderson & Robey (2017).

4.1 Affordances of People Analytics

Our analysis started by identifying three functional roles (with different goals and skills) - managers, employees, and vendors – as potentially important in explaining differences in PA affordances and their actualization. Managers use PA to make data-driven decisions about their workforce, for example, in the area of workforce planning and talent acquisition, aiming to reduce costs and satisfy the workforce. Employees from the HR department use PA to fulfill their operational HR tasks, such as workforce administration and payroll. Vendors do not directly engage with PA, but their perspectives can enhance our understanding of the software vendor's envisioned affordances. The affordances we derived from this analysis are clustered by functional role in Table 4.

Table 4. Affordances of People Analytics by Functional Role

Affordances	**Managers** (ID 1-6, 13-16, 18, 20, 29-31, 35, 37, 40, 41, 43)	**Employees** (ID 7-12, 17, 19, 21-24, 32-34, 36, 38, 39, 42)	**Vendors** (ID 25-28)
PA offers the possibility to control teams via dashboards	+	+	x
PA provides the opportunity to measure employee performance	+	+	
PA supports managers in leading their teams	+	+	
PA provides the possibility to collect more data	+	+	
PA provides the possibility to collect better data	+	x	x
PA supports evidence-based decision-making for managers	+	x	
PA offers the possibility to educate employees via onboarding features	x	x	x
PA provides the opportunity for earlier predictions on workforce development	x	x	x
PA offers the possibility for managers to staff more effectively	x	x	
PA facilitates communication and alignment between managers and employees	x	x	
PA provides the opportunity to integrate different data sources	x		x
PA provides the opportunity to track working times	x		
PA facilitates various use cases depending on users' preferences	x		
PA facilitates the abstraction of data for managers	x		
PA affords the automatization of protocolling tasks	x		

Note: "x" indicates that the affordance was observed in the data, "+" indicates a strong emphasis on the affordance.

4.1.1 Affordance potency

Next, we focused on the potency of the affordances, their perception, and actualization. Affordance potency—referring to the mental and physical energy required to actualize an affordance—varied from low to high potency. Independent of the functional role, actualization requires lots of energy for some individuals and affordances because skills need to be developed, and familiarity with the tool must be established:

> *"For the recruiters, it definitely took a lot of time to familiarize themselves with something new, to learn how to do it and to incorporate it. You can say that our recruiting process became longer with [PA solution], then two months later it became longer again with [another PA solution]. [...] So I would say that the acceptance and adoption of these new tools is actually extremely low"* (ID 17).

In other constellations, the affordance potency is high, leading to the actualization costing little energy:

> *"You always start with a cockpit that contains the most important information for lazy managers. So if they invest even 90 seconds, they have all the information they need. Then there's a reporting section where the most important key figures are calculated and visualized"* (ID 28).

4.1.2 Affordance perception

We derived from the interviews that the identified affordances were perceived in many different ways by different individuals (see Table A2 in the Appendix for a detailed list of affordance perceptions). Leaning towards a positive perception, interviewees point out that "a data-driven HR is making you achieve more accurate decisions" (ID 35) and "in large teams where there are very easily measurable goals, where perhaps performance can also be measured not qualitatively but also quantitatively, it's a great time saver and also enables to treat everyone fairly, even if not equally" (ID 39). The positive-leaning interviewees perceive the affordances around optimizing HR workflows as useful:

"If we have personnel data, […] and digital checklists behind it and generate added value that we can get people through onboarding or through training well, because one person has the possibility to track this and to set actions, that is very helpful" (ID 38).

Others perceive the affordances in a more negative light. For example, some express privacy concerns that come with the actualization of the affordance: "We have to be very sensitive as employees will rather feel tracked and surveilled instead of sensing any advantages" (ID 16). Others fear losing control due to the dashboards and becoming victims of false interpretation:

"*I've seen in many cases that we collected data. And in the team meetings, I can say 100 times: I don't care about the numbers at all!', people will react anyways since there are these numbers. So, it came to a point when I said: 'We won't collect any data anymore for the team dashboard because this biases employees' behavior'*" (ID 8).

4.1.3 Affordance actualization

Lastly, we observed varying degrees of affordance actualization across the interviewees. Some interviewees were still in the early initiation phase of implementing PA and decide consciously not to actualize certain affordances:

"*I personally have nothing to hide. Of course, some of my data is kept in [PA], including personal data, emergency contacts, etc. But, of course, there are also certain access restrictions according to data protection regulations, so that not everyone can see all the data that is personal. So, we also pay close attention to that. In the meantime, this has even gone so far that even birthdays or years of birth are no longer visible" (ID 29).*

Other interviewees have already routinized the use of PA, leading to a high affordance actualization:

"We have actually established a routine. We have monthly reporting. We also have quarterly things and annual things, of course. And we have tried to set up a data model for things that are repeated, so that we don't have to recalculate it every time, that we simply upload the data and it calculates itself […] I think we have already delivered results within 6 months that have led to strategic HR decisions and improved the general decision-making processes" (ID 21).

4.1.4 Unexplained affordance non-actualization

Affordance actualization is generally believed to depend on whether they are in line with users' goals, they are perceived, the users have the skills to actualize them, and their potency is high (Anderson & Robey, 2017; Strong et al., 2014). This established explanation holds for some of our observations, but not for all. Using the case of a representative HR manager, we highlight one anomalous finding. One of our interviewees is responsible for the HR department of a services firm with 50 employees. Her goal is to ensure that all HR-related processes run efficiently and that employee satisfaction is high. She and her team implemented a people analytics solution three years ago, accompanied by supportive training. Thanks to the effective HR change management campaign, the PA tool was mostly perceived positively by her team. The team realized the first successes only three months after the implementation, feeling that the "data-driven workforce of HR is making you achieve more accurate decisions" (ID 35).

At the same time, however, the HR manager had a negative gut feeling about the PA tool:

> "*Yes, well, I would say that it's mixed feelings, 'cause I wanted to migrate the HR department into a very data-driven department in general. I wanted all my processes, I wanted to calculate cost per hire, time to speed, ratio of applicants, gender ratio. So I started getting very much into analyzing everything. [...] But for example, if I was getting the data of [PA], it was always a little complicated, 'cause the software was constantly updating itself and then not getting the accurate information or something I felt that I was not getting. [...] I stopped focusing so much on the data analytics and I started driving my initiatives more towards a people approach, more like an emotional approach to employees, to applicants. [...] That's why it's sort of like not sure where we stand, and I am not sure exactly at this moment how much I want to start implementing the data again*" (ID 35).

These insights cannot be sufficiently explained with the theoretical lens of affordances but motivated our search for alternatives and additional analyses. We next describe how data ideologies can explain the observation around the surprising non-actualization of affordances and unpack the underlying generative mechanisms.

4.2 Data ideologies as an explanation for non-actualization of affordances

In the retroduction step, we revisited our observations and data analyses, searching for other causal explanations. First, we empirically identified codes for the dataist and non-dataist ideologies (Table A3 in Appendix)[3]. Dataist codes center around positive assumptions underlying data in practice (e.g., data are positive, true, accurate, or exhaustive), whereas non-dataists focus on negative assumptions underlying data (e.g., data are inaccurate, subject to interpretation, personal touch is more important). With the data ideologies in hand, we abductively derived three generative mechanisms that are linked to the data ideologies and that influence the actualization of affordances (see Table 5).

Table 5. Generative Mechanisms Impacting Affordance Actualization in People Analytics

Generative mechanism	Description of the generative mechanism	Direction of the generative mechanism based on data ideology
Moderation	Data ideologies **moderate** affordance potency for individuals.	**Dataism:** Heightens the potency of a PA affordance so that it takes less energy to actualize it. **Submechanisms:** 1a: effort rationalization (justifying efforts), 1b: data acceptance bias (trusting data), 1c: transparency-driven potency increase (seeking transparency) **Non-dataism:** Lessens the potency of a PA affordance so that it takes more energy to actualize it. **Submechanisms:** 1d: data completeness barrier (doubting completeness of data), 1e: accuracy-work friction (increasing data workload), 1f: interpretive ambiguity (complicating understanding)
Confirmation	Data ideologies **confirm** the perception of affordances by individuals.	**Dataism:** Acts as a positive lens, confirming prior positive perceptions. **Submechanisms:** 2a: positive outcome reinforcement (confirming positive benefits), 2b: depth perception confirmation (amplifying perceived depth of insights) **Non-dataism:** Acts as a negative lens, confirming prior negative perceptions. **Submechanisms:** 2c: reality disconnect bias (questioning representativeness), 2d: inhumanity perception confirmation (confirming perception of PA being inhuman)
Modulation	Data ideologies **modulate** to which degree affordances are actualized by individuals.	**Dataism:** Modulates the actualization of a PA affordance in an accelerating, holistic manner. **Submechanisms:** 3a: accelerated actualization (speeding up actualization), 3b: outcome justification (overcoming internal resistance), 3c: mandatory actualization (enforcing actualization) **Non-dataism:** Modulates the actualization of an affordance in a decelerating, selective manner.

[3] It is important to note that while we can split the emerging ideologies neatly into two – dataism and non-dataism – based on the predominant beliefs (see Table A3 in the appendix), individual interviewees also expressed mixed sets of beliefs, where their affordance actualization was influenced by both ideologies.

		Submechanisms: 3d: cross-checked actualization (partially actualizing), 3e: context-sensitive actualization (selective based on context)

4.2.1 Mechanism 1: Data ideology moderating affordance potency

The generative mechanism of moderation explains how data ideologies heighten or lessen the potency of datafication technology affordances.

The **positive moderation mechanism** heightens the affordance potency if the underlying data ideology is dataism. It comprises three sub-mechanisms that explain the positive moderation. First, driven by the assumption that data generate new ways to create positive organizational outcomes for individuals themselves or the organization, the moral efforts required to carry out the actualization are decreased, rendering any effort "worthwhile" or even imperative to actualize an affordance (sub-mechanism 1a, effort rationalization). Individuals who exhibit the values that *data are positive* "welcome [people analytics] with open arms" (ID 18). Dataists who think *data provide new insights* "love to see numbers. For them it is much easier to draw conclusions based on statistics compared to an HR gut feeling. So, on that side it is not difficult at all" (ID 21) to implement people analytics systems. Dataists who assume *data are exhaustive* do not see any harm in people analytics: "it would certainly generate a lot of new ideas and new possibilities and ways of looking at people. In this respect, I would first say: it can only do good" (ID 8).

Second, believing that *data are true*, dataists are accepting of any efforts required to actualize datafication technology affordances (sub-mechanism 1b, data acceptance bias). They understand data as mission-critical, as "a lifesaver. [People analytics] is my everyday tool and it's just great how everything keeps updating and getting better. […] I find it super super valuable" (ID 35). Dataists who assume that *data predict the future* and *more data, more value* think that data enable great organizational outcomes including strategic decisions: "[People analytics] makes it possible to correlate internal and external data sources and to make evidence-based, far-reaching decisions" (ID 3).

Finally, since *data are positive* and create fairness and transparency, this creates and increases the energy for individuals to actualize the affordances, moderating the potency (sub-mechanism 1c, transparency-driven potency increase). For example, people analytics facilitates not overlooking employees in large teams, because it "is a great time saver and also a means of treating everyone fairly, not to say equally" (ID 38). Dataists who assume that *data are fair* and *data are positive* extend this perception to others: "We are partly driven by the employees in the direction of more transparency, because and I think that's nice, because […] in their head, transparency is the guarantor of justice and they all want justice in the end or fairness" (ID 14). So, actualizing affordances would create benefits for the others including employees: "we create something that is beneficial for the employee as a result of these analyses, then I can imagine that it is more likely to be adopted" (ID 15). These benefits legitimize any efforts and heighten the affordance potency.

For the **negative moderation mechanism**, we discovered that affordance potency is lessened if the underlying data ideology is non-dataism. Contrary to dataists, non-dataists may argue that investing the effort is not worthwhile: "The only question is what for and what effort I have to put in to generate certain figures and guarantee that they are correct. That's a bit of a catch" (ID 40). The following sub-mechanisms lead to this lowered affordance potency: Non-dataists assume that *data need triangulation* and question the *value of data*. Quantitative data alone is insufficient and qualitative insights are needed, therefore, it is more difficult to actualize the datafication affordances (sub-mechanism 1d, data completeness barrier): "And I think this is always made up of qualitative data that can also be quantified and qualitative data that you simply have to talk about qualitatively in order to derive the right decisions from it" (ID 3).

They believe that *data are not accurate*, but require a lot of data work, lowering the affordance potency (sub-mechanism 1e, accuracy-work friction): "Okay, is the data actually correct? Have we categorized it correctly, entered it correctly, etc. We are still far away from any concerns from employees or conversations with the works council. The primary headache is data quality" (ID 21). The necessary data work lowers the potency of affordances: "very few can use it because the data is often simply too bad or the problem is sitting in front of the computer" (ID 28).

Different interpretations of data can also lower the potency (sub-mechanism 1f, interpretive ambiguity): "the main difficulty is actually in the interpretation of the data that you get. […] I want to decide for myself and therefore want to get the data interpreted as broadly as possible, which is more complex than a simple score" (ID 25).

4.2.2 Mechanism 2: Data ideology confirming perceptions

It is not only about whether a datafication technology affordance is perceived, but also how it is perceived. Thus, as a second generative mechanism, data ideologies confirm the perception of affordances by individuals.

For individuals operating within the dataist ideology, it can confirm their perceptions of datafication technology affordances, acting as a **positive reinforcing lens**. First, dataist assumptions reinforce the perceived outcomes from datafication technology related to more transparency, novel insights, and future predictions (sub-mechanism 2a, positive outcome reinforcement). As dataists assume that *data provide new insights* and data increase transparency, this ideology reinforces their perceptions about data-driven affordances and decision-making:

> *"Yes, I use the data on the one hand to have an overview. I have nine people in my team and it's difficult to keep track of how everyone has developed in each area. I'm not a good person when it comes to memory anyway, so I just need to be able to keep track of everything and because we are generally a very data-driven company"* (ID 42).

Other datafication technology affordances are related to novelty and originality of insights that were previously unknown. A belief that *data provide new insights* is a prerequisite to perceive these affordances related to people analytics: "Accordingly or depending on this, you also have a different focus or a completely different universe where you can start with people analytics everywhere. And ultimately, in my opinion, it's everywhere. So, you can collect figures and improve processes for everything, for every step or every phase of the employee cycle" (ID 18). A related assumption of dataists is that *data predict future*. Individuals believe that forecasts and extrapolation from data to predict future behavior and organizational outcomes are possible. This assumption reinforces the perceptions of datafication technology affordances related to predictions. Dataists appreciate this assumption about data, because to "determine the future path, […] certain trends and evaluations from the past are of course very helpful" (ID 29). For example, it can be used for "forecasting hidden careers, paths or development paths" (ID 27) or arbitrary "early indicators" about the organization's health (ID 2).

Second, dataist assumptions reinforce the perceived outcomes from datafication technology related to unprecedented depths of insights (sub-mechanism 2b, depth perception confirmation). Because *data are exhaustive* and *data are true*, for dataists it is almost self-evident that PA affords deep insights into organizations and humans, for example, "to tell each individual employee how they see the world, what they think is good, what they think sucks, etc." (ID 14). These assumptions reinforce and confirm affordances related to performance management: "The data is used to see how people are performing. In other words, performance is looked at relatively clearly" (ID 34) and crafting "a common view of things" (ID 6) between people. The positive perception of the affordances is reinforced by the assumption that *data are positive*. Data can be "use[d] to control an improved world" (ID 7), because any datafication technology affordance will contribute to making work life be "more objective" (ID 4), "more fact-based [instead of] gut decisions" (ID 2), and "scientifically underpinned" (ID 9).

Like dataism, non-dataism can **confirm underlying perceptions of datafication technologies, but in a negative manner**. Non-dataists assume that *data need triangulation.* The perception of PA affordances is influenced by the belief that data do not show reality (sub-mechanism 2c, reality disconnect bias): "We do look at this and try to provide more than just the bare figures, of course. But it's often still difficult if we don't have the global information on what's happening where in which country" (ID 22). Non-dataists assume that *personal context is more important* than just data, further influencing the perception of datafication technology affordances, because data does not enable truthful or objective actions. A lot of reality may not appear in data, and thus, datafication technology affordances are hindered: "To answer your question, my main impression of the biggest drawback is losing the personal touch. Losing the qualitative input that I get from the employee, it being taken away from the fact that this is a person, first and foremost, this is a person in the company and not a number, and I would be afraid that if I were to make decisions based purely on people analytics then it may not tell the whole story. That would be my sort of main drawback" (ID 36).

Pushed to the extreme, non-dataism confirms the perception of datafication technologies being inhuman (sub-mechanism 2d, inhumanity perception confirmation): "Because it feels like when getting away from humans, like, not making decisions with other humans but rather relying on the computer. And I think that there's more to life than the company achieving maximum growth with maximum profits, and my personal belief is that the people should come first" (ID 36).

4.2.3 Mechanism 3: Data ideology modulating affordance actualization

The third mechanism is that data ideologies modulate to which degree affordances are actualized. While some individuals actualize the affordances quickly and to the full extent, others are more hesitant:

> *"It really depends on the user. I can't recognize a real tendency. There are two camps, so to speak, I would say. Some simply want it to be quick and automatic. The decision is then much easier. And the others are more in favor: We want to make it very human, and we want to stick with it. We want to make decisions much more ourselves, so to speak. So, I would say it's hard to say which way to go. Both. There are even both in one and the same company*" (ID 25).

This suggests two distinct actualization patterns. Dataism **accelerates the actualization** of affordances as individuals are eager to benefit from the outcome (sub-mechanism 3a, accelerated actualization): "I think we have already delivered results within 6 months that have led to strategic HR decisions and improved the general decision-making processes" (ID 21). The outcomes of the rapid actualization are predominantly assessed positively by dataists, as they believe that *data are positive*, which encourages the quick actualization retrospectively:

> *"There's always gonna be a good outcome of course. Just going back to the theory that, of course, if you understand something, then you can only get better from the understanding of*

> *where, why, and how. So, I'm not one of those persons who have like a big issue with my data being analyzed"* (ID 35).

The expectation of good outcomes goes as far as to justify affordance actualization in spite of internal resistance (sub-mechanism 3b, outcome justification). As *data are perceived as fair*, dataists argue: "So if you're worried that we'll mess up the data, then maybe you should think about whether you trust us. It goes both ways, the trust" (ID 31).

This leads to situations where the actualization of PA's affordances is seen as mandatory by dataists (sub-mechanism 3c, mandatory actualization) who believe that *data predict the future*: "And where we have to make ourselves fit for the future and, in my view, the right way to work with high-quality data and thus enable evidence-based decisions, there is no way around it and that also means a high transformation requirement for the HR area" (ID 3).

Conversely, data ideology can also **negatively modulate affordance actualization**. Affordances are only actualized with the necessary triangulation and cross-checking with other approaches, e.g., qualitative data (sub-mechanism 3d, cross-checked actualization). Non-dataists assume that *data need triangulation* and neglecting the qualitative and social aspects is considered "a bit dystopian to me, I would say" (ID 36). As a result, non-dataists avoid actualizing purely data-driven datafication technology affordances. Instead, they opt to combine qualitative and quantitative insights to "look at that [quantitative data] and, of course, try to provide more than just the bare figures" (ID 22).

The findings that *personal context is more important* to non-dataists modulate when and how affordances are selected and actualized (sub-mechanism 3e, context-sensitive actualization). Non-dataists refrain from actualizing affordances that affect existential decisions for individuals (themselves, or employees) and stick to less risky datafication technology affordances:

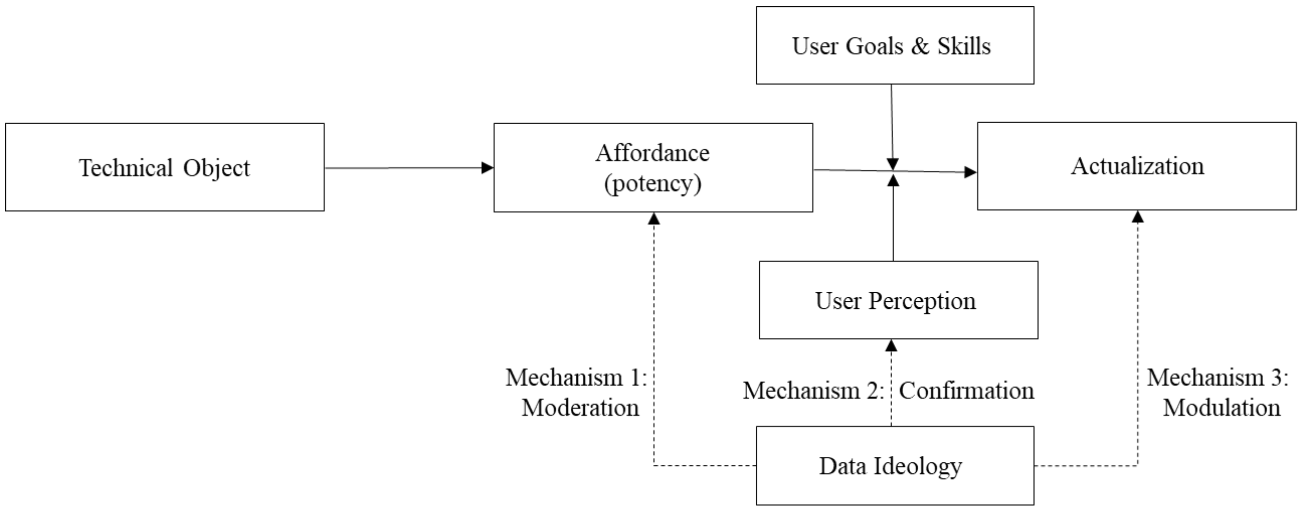
> *"In my time as a leader, it's more been taking a qualitative approach based on each person rather than using data to analyze performance and develop future strategies quantitatively. So yeah, I would say, it's a bit of both. […] We use [people analytics] for our human resources department to basically have like directory of employees and all of the information on that*

but aside from feedback sessions, which I enter into it, so I have like a record of the things I have discussed with the employee" (ID 36).

4.2.4 Revised Explanation of Affordance Actualization

Applying the lens of data ideologies in the retroduction helped us interpret the surprising non-actualization of affordances of datafication technologies, based on the instance of people analytics. While functional roles (i.e. goals), affordance potency, and affordance perception certainly impact the actualization of affordances, data ideologies add another layer of explanatory power to the observations (Figure). The moderation mechanism moderates the potency by effort rationalization, data acceptance, and increased transparency seeking for dataists, or data completeness doubting, accuracy-work friction, and interpretive ambiguity for non-dataists. The confirmation mechanism entails positive outcome reinforcement and depth perception confirmation for dataists, but reality disconnect bias, and inhumanity perception confirmations for non-dataists. Modulation comprises accelerated actualization, outcome justification, and mandatory actualization for dataists, or cross-checked actualization and context-sensitive actualization for non-dataists. We did not observe any mechanism that relates the data ideology to user goals. This non-finding might be explained by the fact that in our data set goals emerge from organizational objectives, where the functional role of the user defines their (business-related) goals, e.g., manager vs. employee vs. vendor. However, in cases where individuals can set their own behavioral goals (e.g., in self-tracking), it might be possible that their goalsetting is also affected by data ideology, especially if the behavioral goals are related to datafication technologies (e.g., as in the phenomenon of the quantified self).

Figure 2. Extension of the Affordances Lens (extending Anderson & Robey, 2017)



5 Discussion

5.1 Alternative Explanations

According to critical realism's multiple determination principle, "no single law 'determines' the whole result" (Elder-Vass, 2010, p. 48). Still, it is possible to come up with good explanations by focusing on "which [causal] powers make the most significant contribution" (Elder-Vass, 2010, p. 178) to the explanandum. To this end, *judgmental rationality* is a core tenet of critical realism, suggesting that, although multiple alternative explanations for an event exist, one explanation can still be more warranted than others (Buch-Hansen & Nielsen, 2020). Here, we address alternative explanations that we discarded.

First, the effect of data ideology may be explained by Ajzen's (1991) concept of subjective norms which "refers to the perceived social pressure to perform or not to perform the behavior" (Ajzen, 1991, p. 188). It relates to social expectations about behaviors in specific situations and is predominantly normative. Social norms affect decision-making by representing what an individual perceives as societal norms for behavior and what close peers believe the individual should do. Although ideologies refer to beliefs and values, the beliefs cover both empirical and normative assumptions. For example, data ideology includes beliefs about what data can and cannot do (empirical), and not just what data should and should not do (normative). Our evidence aligns better with the mechanisms of moderation, confirmation, and modulation, which operate on both empirical and normative beliefs, rather than with the mechanism of subjective norm, which operates only on normative beliefs.

Second, a key question is whether we consider data ideology a *resultant property* (i.e., its causal power is merely inherited from the single beliefs) or if data ideology is an *emergent property* (i.e., causal power is more than the sum of single beliefs). Following *explanatory reductionism*, data ideology is more than the aggregation of single beliefs. Data ideologies have an effect through the relationships between beliefs on data, manifest in the identified generative mechanisms. Therefore, data ideology is an emergent property. In what way the beliefs compose the data ideology, through the mechanisms, through presence and absence of dataist vs. non-dataist beliefs (normative and empirical), "is central to this conception of emergence" (Elder-Vass, 2005, p. 325). This finding is warranted through our empirical data:

- The interplay between different beliefs form the sub-mechanisms.
- Single beliefs can but do not have to be present for a particular individual at any given point in time.
- One individual might have a certain single belief, which another person does not have, yet the generative mechanisms might occur for both of them.
- Single beliefs may have different weights for different individuals.
- Positive and negative beliefs are possible at the same time, showing the complexity of belief systems and the emergent data ideology.
- Finally, the question of whether generative mechanisms would occur for a single belief cannot be answered without looking at the whole, i.e., the data ideology.

Hence, it seems unlikely that the identified mechanisms would occur without data ideology being an emergent property. This counterfactual argument is in line with critical realist analysis because "we cannot distinguish between the causal power of a whole and that of its full set of parts, organized as they are now into that very whole. But we can make a counterfactual distinction between the causal power of a whole and the causal power that its parts would have if they were not organized into such a type of whole" (Elder-Vass, 2010, p. 25).

5.2 Implications for Research on Datafication Technologies and Data Ideologies

Relating our empirical findings to prior (conceptual) research on PA (Giermindl et al., 2022; Tursunbayeva et al., 2018) shows that PA is primarily considered a management technology as conceptualized in theory (Wiener et al., 2019). Previous research considers HR-related tasks, hiring, retention, or onboarding as the predominant application areas without distinguishing the perceptions among different individuals (Hüllmann et al., 2021). Our results corroborate previous research, showing that PA assists managers in leading and managing their teams by enabling evidence-based decision-making (Klöpper & Köhne, 2023) and control through transparency (Hafermalz, 2021). Employees concur with managers and mention that PA enables managerial control. They appreciate the increased transparency, and that PA can supersede mere gut feelings or managerial decision-making, which was previously based on managerial intuitions (Gal et al., 2020). PA also affords employee self-reflection and empowerment, extending the focus on managerial affordances as seen in previous research (Giermindl et al., 2022).

Concomitant with perceptions of functional affordances, novel value-based judgments emerge in our results. While prior conceptual research illustrated the benefits for managers (Tursunbayeva et al., 2018) and negative effects for employees, such as reduced well-being, privacy, and ethics (Gal et al., 2020; Giermindl et al., 2022), our data uncovered nuanced perceptions of datafication technologies. Merely assuming a functional role, e.g., management or employee, is insufficient to explain these varied perceptions of PA. The results show that positive and negative perceptions occur for both managers and employees.

Next to adding nuanced empirical insights to PA as a datafication technology, the study has implications for research on data ideologies. Our results show that the theoretical concepts of dataist and non-dataist put forward by van Dijck (2014) can also be observed empirically. While we do not find evidence for the extreme propositions by Petri (2020), e.g., 'dataists perceive the world as a flow of data,' we find evidence for the more moderate assumptions linked to dataism (Harari, 2017; Petri, 2020). Dataists assume that data are exhaustive and provide novel insights, including predictions for the future. Our findings corroborate theoretical propositions that dataists believe that data allow to "know what you feel" (Harari, 2017, p. 37) and provide an exhaustive representation of the world (Petri, 2020). The findings also corroborate the idea that dataists consider data to be fair, objective, and true, leading to an unconditional belief in data (Jones, 2019; Mari & Petri, 2022). Our empirics add a previously undiscussed assumption for dataists, namely, that they believe that data are positive, yielding favorable societal outcomes. Propositions related to non-dataism have been sparse and positioned as challenging the assumptions of dataism (Jones, 2019; Mikalsen & Monteiro, 2021). While our results also show the challenged assumptions, e.g., that data are inaccurate, the results add a more nuanced understanding of a non-dataist. For instance, non-dataists may not find data valuable at all except for transactional purposes or insist on triangulations citing concerns about varying interpretations giving rise to bias. Ultimately, they favor human touch over numbers.

Our results indicate that data ideologies suggested in theory by Van Dijck (2014) do not exist in pure forms in reality. Instead, it is always a mesh created from tensions between different ideological assumptions. Dataists can appreciate social relationships, while non-dataists can see value in data analytics under certain circumstances. Furthermore, individuals can be pragmatists and refrain from explicit assumptions about data and rather consider data necessary to conduct work. They may also be ambivalent and report facets of dataists and non-dataists equally. Therefore, our results show that data ideologies are not only relevant conceptually (Van Dijck, 2014) or on the societal level (Harari, 2017) but empirically, too. To this end, we extend the theoretical claims that datafication and dataism occur concomitantly by showing that datafication can also co-occur with non-dataism as well (Crooks & Currie, 2021).

5.3 Implications for Research on Affordance Actualization

Investigating PA as an instance of datafication technologies at the workplace, we find that ideologies as a concept can be used to explain the actualization of affordances. Relating these findings to affordance theory, we address Leonardi's call for specifications of the affordance lens instead of pure applications (2023).

Prior works focused on examining the actualization of affordances over time that is shaped by goals and ability (Leonardi, 2013; Markus & Silver, 2008). These investigations have shed light on prerequisites for affordances' actualization in terms of affordance perception, user goals and skills (Strong et al. 2014), and affordance potency (Anderson & Robey, 2017). Despite these insights, extant contributions have suggested that the affordances lens is a valid yet insufficient starting point when interpreting individual or organizational adoption and use of IS (Cheikh-Ammar, 2018; Lichti & Tumasjan, 2023). They suggested adding a value-perspective, focusing on matching underlying values between a technology and individuals next to the perceived affordances.

We follow their idea and position data ideologies as one suitable value-perspective that can help explain why affordances of datafication technologies such as PA are (not) actualized. Our work thereby advances the understanding of the interplay between ideologies and affordances. We introduce ideologies as sets of beliefs that shape how individuals perceive the functional features of technologies, evaluate their potency, and make decisions on their actualization. The generative mechanisms of moderation, confirmation, and modulation extend the theoretical model by Anderson & Robey (2017) (see Figure). They offer a fuller explanation of how value-laden judgments of technologies affect affordance actualization. These insights potentially extend to IT artifacts beyond the class of datafication technology, as we expect the generative mechanisms to be present independent from the specific technology or affordance.

5.4 Practical Contributions

With the surge in datafication, it is crucial to understand how individuals form beliefs about datafication technologies such as PA. Our findings highlight that datafication technologies do not necessarily lead to panoptical control scenarios and an irrevocable subscription to dataism and instead encourage a more heterogeneous discussion of the phenomenon. With that, this study holds meaningful implications for practice.

The introduction of datafication technologies like PA is a necessity within many digital workplace transformations. Due to the sensitive nature of the data and the severe implications on employees, managers should consider the broad set of perceptions when implementing PA. Decision-makers should be aware that managers may not be per se in favor of datafication technology, and, reversely, employees may not be per se against it. As a result, we recommend integrating the workforce at an early stage in the implementation of datafication technologies to avoid misalignment and give voice to concerns. Individual employees should be aware that different ideologies about the capabilities of data exist and shape organizational decision-making. If confronted with datafication technologies, they should reflect on their own generated, collected, and analyzed data and what 'truths' may or may not be derived from the data. Finally, tensions between individuals with different ideologies might arise, and reflecting on the data ideologies may help manage such tensions.

For vendors of datafication technologies, we underline the importance of clearly communicating the technology's utilities as they are interpreted differently by individuals. Providing training on the digital artifact can increase the potency of affordances, however, the individuals' underlying ideologies can still lead to implementation projects failing. We recommend developers of PA to derive the requirements from diverse individuals and test the artifact in different settings, as the underlying ideologies can hardly be predicted.

5.5 Limitations and Outlook

Despite its rigor and relevance, this study has limitations. Methodologically, the sample is limited to German companies. We purposefully selected experts from multiple organizations to collect data from different industries and perspectives; however, gaining in-depth insights into single cases would be valuable to collect more insights on the interdependencies of the different perceptions between individuals. Moreover, the experience of the interview partners with PA varied drastically, which leads to different levels of detail in their interview answers. We accounted for the diverse backgrounds of the interviewees by defining PA in the interviews. To overcome the methodological limitations, we suggest that future research investigates the formation of PA perceptions in longitudinal single case studies and across different regulatory and cultural contexts. Accompanying an organization from the initiation of PA projects to its implementation and use could demonstrate how the beliefs unfold and impact actions over time, providing insights into how data ideologies come about.

Moving beyond these limitations, we purposefully selected PA as a representative instance of datafication technologies. Future studies could examine the phenomenon by selecting different datafication technologies, for example, social process mining (Van der Aalst, 2016). While we interpret datafication technologies broadly—including all types of digital workplace technologies that collect, store, analyze, and act upon individuals' behavioral data—future studies could move beyond the class of datafication technologies and investigate the impact of data ideologies on affordance actualization in contexts outside the workplace. Furthermore, these investigations should not be limited to data ideologies but extend the perspective by studying different types of ideologies. For example, we expect that the ideologies of authoritarianism vs. libertarianism are likely to be influential in actualizing the affordances related to IT-based monitoring systems. When conducting further studies on the impact of ideologies on affordance actualization, the fuzziness between different ideologies always needs to be considered. Investigating tensions between different ideological camps promises interesting avenues for further research. Data ideologies are unconscious compared to prominent and conscious ideologies such as neoliberalism, which are maintained and further developed by an explicit social group (Hartley, 1983). The level of consciousness may moderate how an ideology influences affordance actualization and can be subject of further research.

6 Conclusion

The trend towards datafication seems inevitable at this point. Organizations are increasingly equipped with granular behavioral data on their employees to infer insights about their workforce. We have investigated PA, a representative manifestation of datafication technologies, by interviewing 43 experts to understand how individuals with different functional roles evaluate PA systems regarding their utility and what drives their affordance actualization. Finding that the actualization of perceived affordances could not be sufficiently explained by prior theory, we introduced the concept of data ideologies. With the three identified generative mechanisms of moderation, confirmation, and modulation, data ideologies contribute a valuable extension to affordance theory, explaining how datafication technology affordances are actualized. Enhancing our understanding of how datafication technologies are perceived and implemented across organizations is a crucial first step towards guiding digital workplace transformations. The link between ideologies and affordances may reach beyond dataism and non-dataism and offers promising avenues for future research.

Appendix

Understanding of the Affordance Lens

Given its popularity, multiple notions of affordance theory have emerged that contradict each other. In recent work, Leonardi (2023) reviews common notions of affordances and laments the stagnancy of the affordance theory. The first notion that Leonardi reflects on is *affordance as property* (as a synonym for features or characteristics of a technology). Affordance as property follows Markus & Silver (2008) and suggests that the technical object has affordances independent of the relationship between technology and human. The affordances can be perceived and actualized through human actors. This notion is grounded in the original ideas of Gibson (1977) and is the most used in information systems (e.g., Lehrer et al., 2023; Leidner et al., 2018; Strong et al., 2014).

Leonardi (2023) criticizes that this notion excessively focuses on material properties and not enough on the social aspects. In our reading, however, Leonardi (2023) misrepresents a fundamental tenet of what he calls *affordance as property*. Namely, that technology only has its inherent features and material properties. Instead, we argue – in line with Markus & Silver (2008), Volkoff & Strong (2013), and others – that affordances describe the relationship between technology and humans by emphasizing the independent material properties *and* human actors with their goals in mind. In other words, affordances describe how individuals uniquely perceive, interpret, and appropriate certain material features for their goal-oriented actions. Hence, this paper follows the notion of *affordance as property* based on Strong et al. (2014).

The second notion that Leonardi (2023) summarizes is *affordance as cognition*. This notion is on the other end of the spectrum, the constructivist side, and suggests that affordances are not material but merely interpretations of individuals. It follows a constructivist logic, that is, affordances are "what people think technology will allow them to do" (Leonardi 2023, p. xii), including misunderstandings, misperceptions, and/or misinterpretations (Scarlett & Zeilinger, 2019). According to this notion, perceptions can be formed outside of actually using technology which leads to a prominent focus on humans and their perceptions (Leonardi, 2023).

Leonardi (2023) himself advocates for a third notion: the inseparability of technology usage's material and social aspects, following Orlikowski (1992). Specifically, he rejects Markus & Silver (2008) and states that "affordances are produced through the very action that most scholars presume they enable. Affordances are not action possibilities; they are the ingredients of action" (p. xiii). He claims that affordances only come into being when a technology is being used.

He explains his ontological stance with the underlying philosophical foundation of affordances. Recent works have had two competing philosophical foundations: agential realism and critical realism (Mutch, 2013). Leonardi (2023) follows agential realism, which states that agency is not inherent in any person, place, or thing but materializes through relations. He claims that "agency is 'doing' or 'being'" and not the capability to act or do. However, this study's understanding of agency is, in fact, the ability to do and subsequently the doing; It is not only the doing or being.

Contrary to agential realism as the philosophical foundation for affordances, critical realism has been introduced (Mutch, 2013), which nicely integrates with the *affordance as property* notion. Surprisingly, Leonardi has problematized this very same notion in his earlier works (Leonardi, 2013). In these works, he outlines how critical realism, and affordances can go together to avoid the issues of agential realism. Following his older line of thought, this study applies a critical realism perspective on affordances and the notion of *affordance as property*.

Table A1. Data Ideology versus other concepts concerned with values, norms, and beliefs.

Selected Concept	Differences to Data Ideology
Ideology	Ideologies comprise multiple, interacting beliefs and values, typically associated with economic, social, power, or justice perspectives, that legitimize behaviors. Beliefs can entail normative (i.e., how the world should be) or empirical assumptions (i.e., beliefs about cause and effects).
Data ideology	Data ideology is a single instantiation of ideology with beliefs entailing empirical and normative assumptions on data and how data represent reality. It also legitimizes behaviors related to data.
Subjective norms from theory of planned behavior (Ajzen, 1991)	Subjective norms comprise beliefs about social expectations of behaviors in specific situations. Subjective norms are predominantly normative in content compared to ideology which has a normative and empirical component. Both concepts offer do-s and don't-s.
Culture (Leidner & Kayworth, 2006)	Ideology and culture have overlapping definitions, making it difficult to set them apart. Both operate with implicit assumptions, beliefs, values, and norms, and both have normative and empirical components. However, ideology is distinctly more political and economic with an interrelated, coherent set of ideas about the world (social and political institutions and how they should be). Conversely, culture is reserved for a broader social realm (ethnic, traditional, religious elements) and includes observable artefacts such as language, rituals, and myths.
Mindset (Dweck & Yeager, 2019)	The term is often misused. Mindset theory concerns a single concrete instantiation of a specific belief about whether a person's intelligence is fixed or it can be grown.

Table A2. Perceptions of People Analytics by User Group

Perception	**Managers** (ID 1-6, 13-16, 18, 20, 29-31, 35, 37, 39, 40, 41, 43)	**Employees** (ID 7-12, 17, 19, 21-24, 32-34, 36, 38, 42)	**Vendors** (ID 25-28)
Increased transparency and overview	+	+	x
Improved control	+	+	x
Personalized leadership experience	+	+	
Increased well-being	+	+	
Increased performance and productivity	+	+	x
Increased risk of bad data and unclear validity	+	+	
Increased data quality	+	x	x
Better decisions	+	x	
Increased continuity	x	x	x
Higher ethical/privacy concerns	x	x	x
Unclear legal embedding	x	x	x
Increased objectivity	x	x	x
Value proposition unclear	x	x	x
Increased organizational knowledge	x	x	
More innovative ideas	x	x	
Increased trust	x	x	
Lower trust	x	x	
Increased employee stress	x	+	
More surveillance & reduced safety for employee data	x	x	
Increased unintended effects	x	x	
Increased risk due to wrong interpretations	x		x
Increased flexibility	x		
Improved social relationships	x		
Increased risk of loss of control and algorithm biases			x
More rational insights			x

Note: "x" indicates that the affordances or symbolic expression was perceived, "+" indicates a strong emphasis on the theme.

Table A3. Codes for the Data Ideologies (underlying beliefs)

Data Ideology	Codes	Understanding of the code
Dataism	Data provide new insights	Data facilitate a deep, novel and clear understanding of a phenomenon
	Data are true	Data are in accordance with reality, fact-based and depict a true image of the world
	More data lead to more value	The value of data rises with their amount
	Data are fair	Data are just without favoritism or discrimination
	Data are positive	Data are desirable and their collection and usage lead to favorable outcomes
	Data are exhaustive/holistic	Data depict all facets of a phenomenon and are able to provide a complete image of reality
	Data can identify causality	Data can provide explanations and causes for observed phenomena
	Data predict the future	Data can be used in prescriptive manners such that they predict future trends
Non-dataism	(Personal) context is more important	Personal relationships outweigh the value of data
	Data are inaccurate	Data are incorrect, incomplete and do not depict a true representation of reality
	Data need triangulation	Data need to be enhanced with different information and stand-alone, they do not provide value
	Different interpretations	Interpretations from data can vary and may lead to biases
	Data themselves are not valuable	Data are not desirable and their collection and usage lead to unfavorable outcomes

References

Aaltonen, A., & Stelmaszak, M. (2023). The Performative Production of Trace Data in Knowledge Work. *Information Systems Research*. https://doi.org/10.1287/isre.2019.0357

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Anderson, C., & Robey, D. (2017). Affordance potency: Explaining the actualization of technology affordances. *Information and Organization*, *27*(2), 100–115. https://doi.org/10.1016/j.infoandorg.2017.03.002

Ashforth, B. E., & Kreiner, G. E. (1999). "How Can You Do It?": Dirty Work and the Challenge of Constructing a Positive Identity. *The Academy of Management Review1*, *24*(3), 413–434.

Benbasat, I., Goldstein, D. K., & Mead, M. (1987). The Case Research Strategy in Studies of Information Systems. *MIS Quarterly*, *11*(3), 369. https://doi.org/10.2307/248684

Benlian, A., Wiener, M., Cram, W. A., Krasnova, H., Maedche, A., Möhlmann, M., Recker, J., & Remus, U. (2022). Algorithmic Management. *Business & Information Systems Engineering*, *64*(6), 825–839. https://doi.org/10.1007/s12599-022-00764-w

Bhaskar, R. (2008). *A Realist Theory of Science*. Routledge.

Buch-Hansen, H., & Nielsen, P. (2020). *Critical realism: Basics and beyond* (Macmillan Education, Ed.).

Bygstad, B., Munkvold, B. E., & Volkoff, O. (2016). Identifying Generative Mechanisms through Affordances: A Framework for Critical Realist Data Analysis. *Journal of Information Technology*, *31*(1), 83–96. https://doi.org/10.1057/jit.2015.13

Cheikh-Ammar, M. (2018). The IT artifact and its spirit: a nexus of human values, affordances, symbolic expressions, and IT features. *European Journal of Information Systems*, *27*(3), 278–294. https://doi.org/10.1080/0960085X.2018.1436025

Choi, N., Chengalur-Smith, I., & Nevo, S. (2015). Loyalty, Ideology, and Identification: An Empirical Study of the Attitudes and Behaviors of Passive Users of Open Source Software. *Journal of the Association for Information Systems*, *16*(8), 674–706. https://doi.org/10.17705/1jais.00405

Corbin, J. M., & Strauss, A. (1990). Grounded theory research: Procedures, canons, and evaluative criteria. *Qualitative Sociology*, *13*(1), 3–21. https://doi.org/10.1007/BF00988593

Corbin, J., & Strauss, A. (2008). *Basics of Qualitative Research: Techniques and Procedures for Developing Grounded Theory* (3rd ed.). SAGE Publications, Inc. https://doi.org/10.4135/9781452230153

Crooks, R., & Currie, M. (2021). Numbers will not save us: Agonistic data practices. *The Information Society*, *37*(4), 201–213. https://doi.org/10.1080/01972243.2021.1920081

Daniel, S. L., Maruping, L. M., Cataldo, M., & Herbsleb, J. (2018). The impact of ideology misfit on open source software communities and companies. *MIS Quarterly*, *42*(4), 1069–1096.

DeSanctis, G., & Poole, M. S. (1994). Capturing the Complexity in Advanced Technology Use: Adaptive Structuration Theory. *Organization Science*, *5*(2), 121–147. https://doi.org/10.1287/orsc.5.2.121

Dubois, A., & Gadde, L.-E. (2002). Systematic combining: an abductive approach to case research. *Journal of Business Research*, *55*(7), 553–560. https://doi.org/10.1016/S0148-2963(00)00195-8

Dweck, C. S., & Yeager, D. S. (2019). Mindsets: A View From Two Eras. *Perspectives on Psychological Science*, *14*(3), 481–496. https://doi.org/10.1177/1745691618804166

Elder-Vass, D. (2005). Emergence and the Realist Account of Cause. *Journal of Critical Realism*, *4*(2), 315–338. https://doi.org/10.1558/jocr.v4i2.315

Elder-Vass, D. (2010). *The causal power of social structures: Emergence, structure and agency.* (Cambridge University Press, Ed.).

Ellmer, M., & Reichel, A. (2021). Staying close to business: the role of epistemic alignment in rendering HR analytics outputs relevant to decision-makers. *The International Journal of Human Resource Management*, *32*(12), 2622–2642. https://doi.org/10.1080/09585192.2021.1886148

Gal, U., Blegind Jensen, T., Stein, M.-K., & Blegind, T. (2017). *People Analytics in the Age of Big Data: An Agenda for IS Research* (Vol. 1). http://aisel.aisnet.org/icis2017/TransformingSociety/Presentations/1

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.

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

Gibson, J. J. (1977). The theory of affordances. In *Perceiving, acting and knowing: Towards an ecological psychology* (Erlbaum).

Gierlich-Joas, M., Baiyere, A., & Hess, T. (2024). Inverse Transparency and the Quest for Empowerment through the Design of Digital Workplace Technologies. *Journal of the AIS*, *forthcoming*.

Gierlich-Joas, M., & Zimmer, M. P. (2023). Digital Workplace transformation triggers a shift in the HR identity: from resource manager to growth catalyst. *Proceedings of the 31st European Conference on Information Systems*, 1–16.

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*, *31*(3), 410–435. https://doi.org/10.1080/0960085X.2021.1927213

Glaser, B. G., & Strauss, A. L. (1967). *The discovery of grounded theory: Strategies for qualitative research* (1st ed.). Aldine.

Gregory, R. W., & Muntermann, J. (2011). Theorizing in Design Science Research: Inductive versus Deductive Approaches. *Proceedings of the 32nd International Conference on Information Systems (ICIS)*, 1–17.

Grgecic, D., Holten, R., & Rosenkranz, C. (2015). The Impact of Functional Affordances and Symbolic Expressions on the Formation of Beliefs. *Journal of the Association for Information Systems*, *16*(7), 580–607. https://doi.org/10.17705/1jais.00402

Hafermalz, E. (2021). Out of the Panopticon and into Exile: Visibility and control in distributed new culture organizations. *Organization Studies*, *42*(5), 697–717. https://doi.org/10.1177/0170840620909962

Harari, Y. N. (2017). *Homo Deus. A brief history of tomorrow* (Vintage, Ed.).

Hartley, J. F. (1983). Ideology and Organizational Behavior. *International Studies of Management & Organization*, *13*(3), 7–34. https://doi.org/10.1080/00208825.1983.11656364

Hüllmann, J. A. (2022). Reconciling the Debate on People Analytics in Academia and Practice. *Proceedings of the 35th Bled EConference*, 1–15.

Hüllmann, J. A., Krebber, S., & Troglauer, P. (2021). The IT Artifact in People Analytics: Reviewing Tools to Understand a Nascent Field. In *Proceedings of the 16th International Conference on Wirtschaftsinformatik (WI)* (pp. 238–254). https://doi.org/10.1007/978-3-030-86800-0_18

Huselid, M. A. (2018). The Science and Practice of Workforce Analytics: Introduction to the HRM Special Issue. *Human Resource Management*, *57*(3), 679–684. https://doi.org/10.1002/hrm.21916

Jones, M. (2019). What we talk about when we talk about (big) data. *The Journal of Strategic Information Systems*, *28*(1), 3–16. https://doi.org/10.1016/j.jsis.2018.10.005

Kelly, S., & Noonan, C. (2017). The Doing of Datafication (And What this Doing Does): Practices of Edification and the Enactment of New Forms of Sociality in the Indian Public Health Service.

Journal of the Association for Information Systems, *18*(12), 872–899. https://doi.org/10.17705/1jais.00477

Klöpper, M., & Köhne, S. (2023). Shifting structures – a systematic literature review on people analytics and the future of work. *Proceedings of the 31st European Conference on Information Systems*, 1–19.

Kuckartz, U. (2014). *Qualitative Text Analysis: A Guide to Methods, Practice & Using Software*. SAGE Publications Ltd. https://doi.org/10.4135/9781446288719

Lehrer, C., Constantiou, I., Matt, C., & Hess, T. (2023). How Ephemerality Features Affect User Engagement with Social Media Platforms. *MIS Quarterly*, *47*(4), 1663–1678. https://doi.org/10.25300/MISQ/2023/17085

Leidner, D. E., Gonzalez, E., & Koch, H. (2018). An affordance perspective of enterprise social media and organizational socialization. *The Journal of Strategic Information Systems*, *27*(2), 117–138. https://doi.org/10.1016/j.jsis.2018.03.003

Leidner, & Kayworth. (2006). Review: A Review of Culture in Information Systems Research: Toward a Theory of Information Technology Culture Conflict. *MIS Quarterly*, *30*(2), 357. https://doi.org/10.2307/25148735

Leonardi, P. (2023). Affordances and Agency: A Clarification and Integration of Fractured Concepts. *MIS Quarterly*, *47*(4), 9–20.

Leonardi, P., & Contractor, N. (2018). Better People Analytics. *Harvard Business Review*, *96*(6), 70–81.

Leonardi, P. M. (2013). Theoretical foundations for the study of sociomateriality. *Information and Organization*, *23*(2), 59–76. https://doi.org/10.1016/j.infoandorg.2013.02.002

Lichti, C. W., & Tumasjan, A. (2023). "My Precious!": A Values-Affordances Perspective on the Adoption of Bitcoin. *Journal of the Association for Information Systems*, *24*(3), 629–663. https://doi.org/10.17705/1jais.00790

Mari, L., & Petri, D. (2022). Measurement, Dataism and Post-Truth Ideology: The Good, The Bad and The Ugly. *IEEE Instrumentation & Measurement Magazine*, *25*(7), 3–6. https://doi.org/10.1109/MIM.2022.9908261

Markus, M. L., & Silver, M. (2008). A Foundation for the Study of IT Effects: A New Look at DeSanctis and Poole's Concepts of Structural Features and Spirit. *Journal of the Association for Information Systems*, *9*(10), 609–632. https://doi.org/10.17705/1jais.00176

McAfee, A., & Brynjolfsson, E. (2012). Big data: the management revolution. *Harvard Business Review*, *90*(10), 60–68.

McCartney, S., & Fu, N. (2022). Bridging the gap: why, how and when HR analytics can impact organizational performance. *Management Decision*, *60*(13), 25–47. https://doi.org/10.1108/MD-12-2020-1581

Mettler, T. (2023). The connected workplace: Characteristics and social consequences of work surveillance in the age of datification, sensorization, and artificial intelligence. *Journal of Information Technology*. https://doi.org/10.1177/02683962231202535

Mikalsen, M., & Monteiro, E. (2021). Acting with Inherently Uncertain Data: Practices of Data-Centric Knowing. *Journal of the Association for Information Systems*, *22*(6), 1715–1735. https://doi.org/10.17705/1jais.00722

Mingers, J. (2004). Realizing information systems: critical realism as an underpinning philosophy for information systems. *Information and Organization*, *14*(2), 87–103. https://doi.org/10.1016/j.infoandorg.2003.06.001

Mirbabaie, M., Stieglitz, S., & Frick, N. R. J. (2021). Hybrid intelligence in hospitals: towards a research agenda for collaboration. *Electronic Markets*, *31*(2), 365–387. https://doi.org/10.1007/s12525-021-00457-4

Möhlmann, M., Zalmanson, L., Henfridsson, O., & Gregory, R. W. (2021). Algorithmic Management of Work on Online Labor Platforms: When Matching Meets Control. *MIS Quarterly*, *45*(4), 1999–2022. https://doi.org/10.25300/MISQ/2021/15333

Mueller, B., & Urbach, N. (2017). Understanding the Why, What, and How of Theories in IS Research. *Communications of the Association for Information Systems*, *41*, 349 – 388.

Mutch, A. (2013). Sociomateriality — Taking the wrong turning? *Information and Organization*, *23*(1), 28–40. https://doi.org/10.1016/j.infoandorg.2013.02.001

Ngwenyama, O., Rowe, F., Klein, S. , & Henriksen, H. Z. (2023). The Open Prison of the Big Data Revolution: False Consciousness, Faustian Bargains, and Digital Entrapment. Information Systems Research. *Information Systems Research*.

Nyman, S., Bødker, M., & Blegind Jensen, T. (2023). Reforming work patterns or negotiating workloads? Exploring alternative pathways for digital productivity assistants through a problematization lens. *Journal of Information Technology*. https://doi.org/10.1177/02683962231181602

Orlikowski, W. J. (1992). The Duality of Technology: Rethinking the Concept of Technology in Organizations. *Organization Science*, *3*(3), 398–427. https://doi.org/10.1287/orsc.3.3.398

Orlikowski, W. J. (2000). Using Technology and Constituting Structures: A Practice Lens for Studying Technology in Organizations. *Organization Science*, *11*(4), 404–428. https://doi.org/10.1287/orsc.11.4.404.14600

Parmiggiani, E., Østerlie, T., & Almklov, P. G. (2022). In the Backrooms of Data Science. *Journal of the Association for Information Systems*, *23*(1), 139–164. https://doi.org/10.17705/1jais.00718

Patton, M. Q. (2002). Two Decades of Developments in Qualitative Inquiry. *Qualitative Social Work*, *1*(3), 261–283. https://doi.org/10.1177/1473325002001003636

Petri, D. (2020). Big data, dataism and measurement. *IEEE Instrumentation & Measurement Magazine*, *23*(3), 32–34. https://doi.org/10.1109/MIM.2020.9082796

Polzer, J. T. (2022). The rise of people analytics and the future of organizational research. *Research in Organizational Behavior*, *42*, 100181. https://doi.org/10.1016/j.riob.2023.100181

Saldana, J. (2009). *The coding manual for qualitative reseachers* (1st ed.). SAGE Publications Ltd.

Scarlett, A., & Zeilinger, M. (2019). Rethinking affordance. *Media Theory*, *3*(1), 1–48.

Schafheitle, S. D., Weibel, A., Ebert, I. L., Kasper, G., Schank, C., & Leicht-Deobald, U. (2020). No stone left unturned? Towards a framework for the impact of datafication technologies on organizational control. *Academy of Management Discoveries*, *6*(3), 455–487. https://doi.org/10.5465/amd.2019.0002

Strong, Volkoff, O., Johnson, S., Pelletier, L., Tulu, B., Bar-On, I., Trudel, J., & Garber, L. (2014). A Theory of Organization-EHR Affordance Actualization. *Journal of the Association for Information Systems*, *15*(2), 53–85. https://doi.org/10.17705/1jais.00353

Tams, S., Ahuja, M., Thatcher, J., & Grover, V. (2020). Worker stress in the age of mobile technology: The combined effects of perceived interruption overload and worker control. *The Journal of Strategic Information Systems*, *29*(1), 101595. https://doi.org/10.1016/j.jsis.2020.101595

Trice, H. M. , & Beyer, J. M. (1993). *The cultures of work organizations*. Prentice-Hall, Inc.

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*(July), 224–247. https://doi.org/10.1016/j.ijinfomgt.2018.08.002

Van der Aalst, W. (2016). Data Science in Action. In *Process Mining* (pp. 3–23). Springer Berlin Heidelberg.

Van Dijck, J. (2014). Datafication, dataism and dataveillance: Big Data between scientific paradigm and ideology. *Surveillance & Society*, *12*(2), 197–208. https://doi.org/10.24908/ss.v12i2.4776

Volkoff, O., & Strong, D. M. (2013). Critical Realism and Affordances: Theorizing It-Associated Organizational Change Processes. *MIS Quarterly*, *37*(3), 819–834.

Volkoff, O., & Strong, D. M. (2017). Affordance theory and how to use it in IS research. In *The Routledge companion to management information systems*. Routledge.

Wang, B., Schlagwein, D., Cecez-Kecmanovic, D., & Cahalane, M. (2020). Beyond the Factory Paradigm: Digital Nomadism and the Digital Future(s) of Knowledge Work Post-COVID-19. *Journal of the Association for Information Systems*, *21*, 1379–1401. https://doi.org/10.17705/1jais.00641

Werkhoven, J. A. (2017). *Exploring Functional Affordances and Sensemaking in Human Resource Analytics Full Paper*.

Wiener, M., Mähring, M., Remus, U., Saunders, C., & Cram, W. A. (2019). Moving IS Project Control Research into the Digital Era: The “Why” of Control and the Concept of Control Purpose. *Information Systems Research*, *30*(4), 1387–1401. https://doi.org/10.1287/isre.2019.0867

Wiesche, M., Jurisch, M. C., Yetton, P. W., & Krcmar, H. (2017). Grounded Theory Methodology in Information Systems Research . *MIS Quarterly*, *41*(3), 685–702.

Wynn, & Williams. (2012). Principles for Conducting Critical Realist Case Study Research in Information Systems. *MIS Quarterly*, *36*(3), 787. https://doi.org/10.2307/41703481