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EVERY BREAK YOU TAKE, EVERY CLICK YOU MAKE - EMPIRICAL INSIGHTS ON EMPLOYEES' PERCEPTION OF PEOPLE ANALYTICS

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Research Paper

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Abstract

As work becomes increasingly decentralised, employers and employees alike are searching for tools that support (self-) organising and leadership in dispersed teams. Therefore, people analytics, as a form of algorithmic management, is increasingly gaining popularity. However, besides the alleged potential held by people analytics, it also has an inherent potential to serve as surveillance software and to perpetuate existing biases and discrimination. Whilst vendors of people analytics software provide a positive narrative and researchers from different disciplines provide extensive literature reviews, empirical insights remain scarce. Falling back on privacy calculus theory, we develop a research model to explain employees' perception of people analytics deployment in their workplace. Leveraging insights from a scenario-based online survey, we find that employees overwhelmingly disagree with the concept of people analytics. Implementing people analytics causes privacy concerns and erodes employees' trust in their organisation to a level where they are likely to consider leaving the company.

Keywords: People Analytics, Future of Work, Privacy Calculus, Scenario-based Survey.

1 Introduction

Accelerated by the sudden need to decentralise work caused by the outbreak of the COVID-19 pandemic in early 2020, companies increasingly deployed different approaches of algorithmic management, such as people analytics (PA) (Leonardi, 2021; Adams-Prassl, 2022; Bryce, McBride and Cunden, 2022). PA can be defined as the deployment of descriptive, predictive, or prescriptive analytics to generate insights into an organisation's workforce and to give recommendations for action, thereby optimising decision-making, performance and employee experience (Gal et al. 2020; Giermindl et al. 2021). Whilst algorithmic management previously had a strong connection to gig work and the management of platform workers (e.g., Uber, Deliveroo drivers), PA is now also prevalent in traditionally office-based work settings (Adams-Prassl, 2022). PA systems continuously collect data generated by employees, such as the number of emails sent, time spent in meetings, or hours worked outside of regular work hours (Gal et al., 2020). Based on the data, the systems provide overviews of, for instance, the productivity or interaction of teams as well as attrition risks or candidates for training measures. The collected data might then be processed and used for further analyses by merging it with datasets accumulated over time within the company (Gal et al., 2020; Jarrahi et al., 2021; Meijerink, Boons, Keegan and Marler, 2021). Thus, the deployment of PA promises to not only enable the management of decentralised teams and gain actionable insights into a workforce but also to decrease human biases and resulting discrimination as decisions are made on the premise of supposedly neutral algorithms (Giermindl et al., 2021; Klöpper and Köhne, 2022; Tursunbayeva, Pagliari, Di Lauro and Antonelli, 2022). However, researchers have pointed out that the actual negative effects of PA might outweigh the potential benefits of the systems (Adams-Prassl, 2022; Klöpper and Köhne, 2022). Some PA systems are even described as surveillance software: they record and analyse keystrokes, access cameras and microphones, and take frequent screenshots (Schlagwein and Jarrahi, 2020; Tursunbayeva et al., 2022). This is especially relevant in the context of remote work. As traditional workplace structures are currently shifting and remote work becomes the “new normal” for many employees, companies look for tools that replace traditional approaches for measurement of performance or compliance with working hours (Leonardi, 2021). Depending on the underlying training data, PA systems are also able to perpetuate existing biases and social injustice, which contradicts the promises made by vendors to reduce said risks (Gal et al., 2020; Giermindl et al., 2021; Tursunbayeva et al., 2022). Aside from the emerging risks for employees, team leaders could potentially experience a loss of control after a first stage of empowerment (Giermindl et al., 2021), rooted in a loss of trust by their employees, who might increasingly consider the algorithmic system as the decision maker, as opposed to the supervisor (Chiu, Zhu and Corbett, 2021; Tomprou and Lee, 2022).

The body of literature on PA is rapidly growing. However, whilst researchers increasingly focus on the perils and downsides of PA (e.g., Adams-Prassl 2022; Gal et al. 2020; Giermindl et al. 2021; Tursunbayeva et al. 2021) and also dedicate scholarly attention towards the topic of algorithmic biases and discrimination (Floridi and Strait, 2020; Manokha, 2020; Marjanovic, Cecez-Kecmanovic and Vidgen, 2021, 2022; Tsamados et al., 2022), research on the emerging risks of PA for employees remains scarce (Tursunbayeva et al., 2018; Jarrahi et al., 2021; Bryce et al., 2022; Klöpper and Köhne, 2022; Miceli, Posada and Yang, 2022). The majority of studies on PA are not empirical, peer-reviewed studies but rather discussion papers, technical descriptions, or blog posts, often written by industry sources such as the vendors of PA themselves (Tursunbayeva et al., 2018; Giermindl et al., 2021). There are only few empirical studies predominantly looking at the topic of acceptance of algorithmic leadership and advice (e.g. Höddinghaus, Sondern and Hertel, 2021; Tong, Jia, Luo and Fang, 2021; Tomprou and Lee, 2022) or the process of adoption and implementation of algorithmic personnel management (Shet, Poddar, Wamba Samuel and Dwivedi, 2021; e.g. Miceli et al., 2022). Quantitative approaches towards understanding the phenomenon PA are scarce. In a recent editorial of a special issue of the human resources management journal, Edwards and colleagues consequently remarked on the paradox that, whilst the number of reviews on the matter is rapidly growing, there is a substantial lack of empirical research to draw on (Edwards, Charlwood, Guenole and Marler, 2022). Further, the perspective of employees on PA is currently vastly missing from the scientific and general debate. Whilst, as outlined above, a vast number of potential risks of PA have been identified by researchers, the discourse currently evolves without accounting for the perspective of the employees. Thus, PA might well be deployed with good intentions; the current state of knowledge prevents an employee-centric use of the technology. Investigating the impact PA implementation has on employees is therefore a timely and necessary endeavour. Against this backdrop, we formulate the research question: *How does PA implementation affect employees' perception of their employer?*

To guide our research endeavour, we adopt the extended privacy calculus model (EPCM) by Dinev and Hart (2006), which was developed for examining individual consumers' intention to share private information in online transactions. We transfer the model to the context of employees' perception of PA system implementation at their workplace. We evaluate our research model by conducting a scenario-based online survey. Participants take the role of employees facing the situation that their company deploys a PA system. Our results show that the PA system raises privacy concerns and erodes employees' trust in their organisation to a level where they are likely to consider leaving the company. The contribution of the paper is threefold. First, by providing a theoretical foundation for explaining employee perception of PA systems in their workplace. Second, our survey-based approach provides the first empirical insights into the realm of PA research. Third, we derive several practical implications for both organisations and PA developers on the importance of incorporating an employee perspective into deploying and creating PA systems.

2 Related Work and Theoretical Foundations of PA

PA places an increased value on the ranking, classification, and measurement of workers' performance, much like traditional management approaches such as Taylorism and Fordism. The use of data science to collect, analyse and visualise employee-generated data enables detailed insight into the productivity of both individual workers and whole teams and workforces (Tursunbayeva et al., 2022). PA systems increasingly incorporate features based on sophisticated statistical models, such as machine learning (ML) or AI (Giermindl et al., 2021). Prominent use cases of PA are found in every stage of employees' life cycle in a company. These include the screening of CVs during the onboarding, the analysing of performance data and resulting personalised recommendations for future trainings, the prediction of unwanted fluctuation and retention, or suggestions of potential raises (Gal, Jensen and Stein, 2017; Marler and Boudreau, 2017; Tursunbayeva, Pagliari, Lauro and Antonelli, 2019; Giermindl et al., 2021). Another increasingly popular use case is employee-wellbeing. The application of PA is often connected with the desire of increasing job satisfaction and the reduction of work-related stress (Gal et al., 2020). Though, as Tursunbayeva and colleagues point out, the systems might well be represented as means of promoting employee wellbeing and experience, while in fact, they can foster drastic forms of surveillance (Tursunbayeva et al., 2022). Also, as Gal et al. (2017) describe, viewing and treating employees as quantified data and not as individual human beings stands in contrast to humanistic management approaches. The discourse around PA is currently driven by industry sources and vendors of PA (Tursunbayeva, 2020). Scientific studies come mainly from the management discipline, though studies on PA from the Information Systems and computer sciences communities are increasing. Large parts of those publications coming from industry sources contain advertising promises and praise PA for its alleged objectiveness and efficiency (Tursunbayeva et al., 2019). Studies on the perils and risks of PA are increasing, but they cannot outnumber the many positive and technocentric approaches.

PA and the way it is advertised and discussed can therefore lead to incorrect assumptions about the reliability and objectiveness of algorithmic management (Leicht-Deobald et al., 2019; Giermindl et al., 2021). In addition, the systems pose a fundamental threat to employees' privacy (Manokha, 2020; Bryce et al., 2022; Weiskopf and Hansen, 2022). In the context of remote work, the invasion of privacy even goes beyond matters of data privacy, as employees become constantly 'visible' for their employers, even in the setting of their own homes (Klöpper and Köhne, 2022).

There are three different maturity levels of current PA systems: 1. *descriptive analytics,* which uses standard statistical methods (e.g. correlation analysis, simple regressions, mean values) to analyse current and historical data and, therefore, supports companies in understanding their current performance as well as potential problems (Leicht-Deobald et al., 2019; Giermindl et al., 2021), 2. *predictive analytics,* which also analyses current and historical data. However, it deploys more advanced methods (e.g. data mining, advanced regressions) to predict trends and events that will happen in the future, usually by providing a likelihood score of certain outcomes (Leicht-Deobald et al., 2019; Schafheitle, Weibel and Rickert, 2020; Giermindl et al., 2021), and 3. *prescriptive analytics,* which deploys machine learning (ML) algorithms to provide actionable insights (Tursunbayeva et al., 2019). It goes beyond predicting trends and events but recommends actions that influence the outcome of the predicted events (Giermindl et al., 2021). Next, maturity in this context refers to the potential analytical capacity of a system (Giermindl et al., 2021). Giermindl and colleagues (2021) also propose a fourth maturity level, autonomous analytics, that autonomously performs the given recommendations. In the context of this study, however, we only account for the first three maturity levels, as the fourth is not commonly deployed within PA systems yet.

Whilst a substantial amount of literature on PA exists, the majority of research contributions look at PA from a strictly theoretical lens. Empirical work is scarce. Multiple literature reviews on the topic have emerged in recent years (Marler and Boudreau, 2017; Tursunbayeva et al., 2018; Chalutz Ben-Gal, 2019; Giermindl et al., 2021; Margherita, 2022). Though, as Edwards and colleagues (2022) pointed out, the existing amount of reviews surpasses the amount of content to be reviewed. Matters of privacy in the context of PA and other forms of algorithmic management are discussed theoretically, whilst the (user) perspective of the employees is vastly missing from peer-reviewed literature. Studies that empirically investigate single aspects of algorithmic (human resource) management provide valuable first insights. For example, Lee (2018) looked at the perceived fairness of algorithmic decisions at the workplace, and Kaibel and colleagues (2019) investigated applicants' perceptions of hiring algorithms. Notably, Tomprou and Lee (2022) investigate the psychological aspects of algorithmic decision-making in a series of studies. Studies that investigate employees' perceptions of PA systems or system implementation are missing. PA, with its capability to serve as a surveillance tool, holds different social and ethical implications than other aspects of algorithmic decision-making at the workplace. It combines all the aforementioned risks stemming from potentially biased algorithmic decision-making with the risks stemming from constant monitoring. Therefore, there is a clear gap within the field of research on PA, which this paper addresses accordingly.

3 Research Model and Hypotheses Development

The theoretical lens for developing our research model is Dinev and Hart's (2006) EPCM. The EPCM provides insights into the influence of contradicting beliefs on consumers' intention to share personal information within Internet transactions. They follow a long tradition of IS research, where antecedents of behavioural intention have been one major research topic for decades (e.g., Davis 1989; Davis et al. 1989; Venkatesh et al. 2003). The EPCM originates from Fishbeins and Azjen's (1977) theory of reasoned action and Azjen's (1980) theory of planned behaviour. The model comprises five constructs, which can be clustered into three construct categories: 1. Risk beliefs, comprising perceived Internet privacy risk, reflecting a belief that amounts to an assessment of, for instance, an Internet website, and Internet privacy concerns, reflecting an "internalization of the possibility of loss, for instance, disclosed personal information (Dinev and Hart, 2006, p. 65). 2. Confidence and enticement beliefs, comprising Internet trust and personal internet interest, and 3. Willingness to act, comprising willingness to provide personal information on the Internet. Within the EPCM, risk beliefs relate specifically to a potential loss of privacy. Thereby, they contrast earlier studies examining risks in (online) transactions mainly by measuring it in a rather generic manner or by exclusively considering financial losses (Dinev and Hart, 2006). Exemptions from this are, for instance, Pavlou and Gefen (2004), who note that the impact of perceived privacy risks might be higher than economic risks in influencing consumer decisions on whether or not to enter an Internet transaction. Confidence and enticement beliefs, though they do not cancel out the risk beliefs, might be the predominant factor in influencing willingness to act. Especially trust, as an established and well-researched construct, can positively influence decision-making (Bolton, Katok and Ockenfels, 2004; Pavlou and Gefen, 2004). Willingness to act in the EPCM, however, differs from earlier approaches to examining behavioural intentions. In so, Dinev and Hart (2006) explicitly stress the intention to provide personal data as a premise for entering Internet transactions. They argue that the (potentially contradictory) beliefs of a person may influence each other to a point where one belief surpasses. This reasoning, however, does not eradicate the strength of the remaining beliefs. Therefore, all existing beliefs together form a calculus, where the different beliefs are summed up (Laufer and Wolfe, 1977; Culnan and Armstrong, 1999). Dinev and Hart's (2006) results imply that, in a decision process, privacy concerns can be outweighed by the aggregated influence of trust and personal interest. We adopt and extend the EPCM to a context of employees' perception of PA system implementation in their workplace environment. The lens of the EPCM, thus, is a natural fit for our endeavour to investigate the influence of multiple factors (i.e., perceived risks, perceived usefulness) that employees might have to consider when they are confronted with the introduction of a PA system. However, in contrast to consumers in Internet transactions, employees cannot, or only to a limited extent, choose which tools they prefer to use. Thus, the ultima ratio for employees who are not willing to "transact" with a PA system would be to leave the company. In the following, we elaborate on the development of our research model (Figure 1), and all included hypotheses.

***Influence of Perceived PA perils on perceived PA privacy risk*—**Giermindl and colleagues (2021) identified a conclusive set of six perils that can emerge from deploying PA: *Illusion of control and reductionism* (e.g., overconfidence in the systems can lead to blind trust in and resulting poor decision-making), *estimated predictions and self-fulfilling prophecies* (e.g., recommendations might confirm previously made, potentially wrong, assumptions, leading to a self-affirming circle), *fostering of path-dependencies* (e.g., prediction of events based on data from the past can hinder processes of innovation), *impairment of transparency and accountability* (e.g., human managers are still responsible if discrimination occurs, but it is difficult to detect the underlying source of it), *reduced autonomy of* *employees* (e.g., automated management processes can replace human decision-making), *marginalisation of human reasoning and reduced managerial competences* (e.g., managers might feel pressured into acting on the recommendations and might thus lose their managerial competencies). We argue that those perils constitute a consequence of opportunistically utilising personal information in a way that was not foreseeable for employees. PA systems constantly collect employee-generated data: in addition to tracking non-traditional metrics like emails, biometrics, contact information, or social media activity, businesses are constantly looking for new ways to monitor employee behaviour (e.g., Giermindl et al., 2021; Raveendhran and Fast, 2021). Some systems even gather and analyse keystrokes, screenshots, and log-in times to offer perceptions of employee 'productivity' (Jarrahi et al., 2021). It might become less transparent for employees how and why decisions are made and how their data influenced these decisions (Giermindl et al., 2021; Adams-Prassl, 2022; Tursunbayeva et al., 2022). PA systems thereby constitute an inherent privacy risk for employees. In line with the EPCM, privacy risks not only include the misuse of personal information in unintended ways but also opportunistic behaviour (Rindfleisch, 1997). As such, we argue that the capabilities of a PA system, and the thereby perception of emerging perils, directly determine the perceived privacy risks emerging from it. Consequently, our first hypothesis is: **H$_1$**: *A higher level of Perceived PA perils has a positive effect on perceived PA privacy risk.*

Influence of Perceived PA perils on perceived usefulness of PA**—**as Davis (1989) argues, a system with a high level of perceived usefulness is consequently a system with a perceived beneficial use-performance relationship. At the workplace, this could be an increase in productivity which subsequently might be followed by a promotion or a raise. And indeed, the existence of a PA system can generate usefulness for employees to a certain extent. They can be used to prevent excessive workload and potentially resulting burnout, or to motivate employees to be more self-reflective to work more productively overall. However, the deployment of PA might have more potential drawbacks than positive effects for employees (Parent-Rocheleau and Parker, 2021). For example, biases, prejudice, and social injustice can be reinforced and sustained by the systems' underlying algorithms (e.g., Gal et al., 2017; Giermindl et al., 2021; Tursunbayeva et al., 2022). With the amount of data monitoring through the PA system, employees can feel overly pressured into higher productivity, which is not sustainable and might only lead to short-term increases in performance (Manokha, 2020; Tursunbayeva et al., 2022). Due to the system's intransparency, employees might not understand the reasoning behind beneficial actions such as promotions or raises. Overall, we argue that PA system's usefulness is directly determined by the perils it poses. The greater the perils posed by a PA system, the lesser the usefulness associated with it. Formally: **H$_2$**: *A higher level of perceived PA perils has a negative effect on perceived usefulness of PA system.*

Influence of PA privacy risk on PA privacy concerns**—**some PA systems are highly invasive and are even described as surveillance tools (Manokha, 2020; Klöpper and Köhne, 2022; Tursunbayeva et al., 2022). PA is based on the premise of collecting employee-generated data. However, it might not be transparent for employees what kind of data is collected or how it is processed (Giermindl et al., 2021; Tursunbayeva et al., 2022), resulting in perceptions of privacy risk and privacy concerns. As Dinev and Hart (2006) point out, privacy risk and concerns are closely related. While the perceived privacy risks refer to an overall assessment of the PA system, the authors delineate privacy concerns as "beliefs about who has access to information that is disclosed" (Dinev and Hart, 2006, p. 65). As the risk (or uncertainty) about potential misuse of the data employees have to disclose within the PA system increases, privacy concerns increase. In the context of PA, a high uncertainty on the employee's side is likely to exist, as access to their data or information about how and which decisions were derived from it is often limited. PA systems with high levels of perceived privacy risk should only foster those concerns. Consequently, our next hypothesis states: **H$_3$**: *A higher level of perceived PA privacy risk has a positive effect on PA privacy concerns.*

Influence of PA privacy risk on intention to leave company**—**originally, the EPCM examines individuals' willingness to enter Internet transactions. Those transactions are usually decisions made on the premise of individuals' free will – they do not *have* to use a specific service. However, in the case of workplace and PA deployment, the option of usage refusal is usually not given. Employees in a company commonly cannot decide independently whether they want to use a technical system or not (Orlikowski, 1992). In order to prevent the sharing of their own data with the system, the opt-out option in the ultima ratio is to leave the company and find a job without a PA system in place. Therefore, we operationalise this construct of choosing not to "use" the PA system with the intention of leaving the company. As within the EPCM, perceived PA privacy risk should positively influence the ultimate decision to not conform with a workplace utilising a PA system. We hypothesise: $\mathbf{H_4}$: *A higher level of perceived PA privacy risk has a positive effect on intention to leave company.*

Influence of PA privacy risk on trust in organisation**—**trust as a multidimensional construct has been found by Gefen and colleagues (2003) to have a direct positive relationship with the intention to share private information. At the same time, low levels of perceived risks when sharing private information are associated with higher levels of trust in the other party (Dinev and Hart, 2006). In the original EPCM, this reference is represented by trust in the underlying system (i.e., the Internet). In the context of our study, the other party or the underlying structure is the organisation (i.e., the employees' workplace) itself. An increasing (perceived) source of risk in the working environment might well lead to employees perceiving the environment as less safe, resulting in an overall loss of trust in the entity providing and shaping their working environment. Thereby, a belief that PA is non-reliable, unsafe, and handles information in an incompetent fashion should influence employees' trust in the organisation. Consequently, our next hypothesis is: $\mathbf{H_5}$: *A higher level of perceived PA privacy risk has a negative effect on trust in organisation.*

Influence of PA privacy concerns on intention to leave company**—**Dinev and Hart (2006) outline that when perceived privacy concerns are high, the behavioural intention not to disclose private information is also high. In line with the notion provided by expectancy theory (Van Eerde and Thierry, 1996), individuals have a high motivation to minimise potential negative outcomes for them. In our context, employees who seek to prevent uncertainty of potential misuse of their data presumably are more inclined to leave the company due to their concerns. This would be in line with previous research outlining concerns regarding restricted work-related data privacy causes increases in employees' work intensity (Manokha, 2020), stress level (Parent-Rocheleau and Parker, 2021), and overall job dissatisfaction (Tursunbayeva et al., 2022). Consequently, we expect concerns in this realm to impact the intention to stay at a company directly. We hypothesise: $\mathbf{H_6}$: *A higher level of PA privacy concerns has a positive effect on intention to leave company.*

Influence of trust in organisation on intention to leave company**—**Trust in an organisation captures employees' expectations regarding the company's integrity, consistency, and benevolence towards them, based on their accumulated previous experiences with them (Gabarro and Athos, 1976; Dirks and Ferrin, 2001; Lumineau, 2017). Thereby, trust in the organisation constitutes a fundamental component for employees to shape their perception of and relationship with the organisation. Since employees also use their trust perceptions as a proxy for predicting future company behaviour (Dirks and Ferrin, 2001; Crossley, Cooper and Wernsing, 2013), we expect that the level of trust has a direct impact on the intention to leave the company. Thereby, we hypothesise: $\mathbf{H_7}$: *A higher level of trust in organisation has a negative effect on intention to leave company.*

Influence of perceived usefulness of PA on intention to leave company**—**system usefulness has been shown numerous times to be a meaningful antecedent of actual usage. (Davis et al., 1989; Venkatesh et al., 2003). However, as outlined before, employees' influence on deciding whether or not to use a deployed system at the workplace is limited (Orlikowski, 1992). Though, the usefulness of a system at work genuinely implies that it facilitates employees' work, benefiting their overall well-being or productivity. However, if the system is perceived as useful, then its implementation should be in the interest of employees. In turn, this implementation by the company should be perceived as an act of support and, thus, negatively impact the intention to leave. Consequently, we articulate the hypotheses: $\mathbf{H_8}$: *A higher level of perceived usefulness of PA system has a negative effect on intention to leave company.*

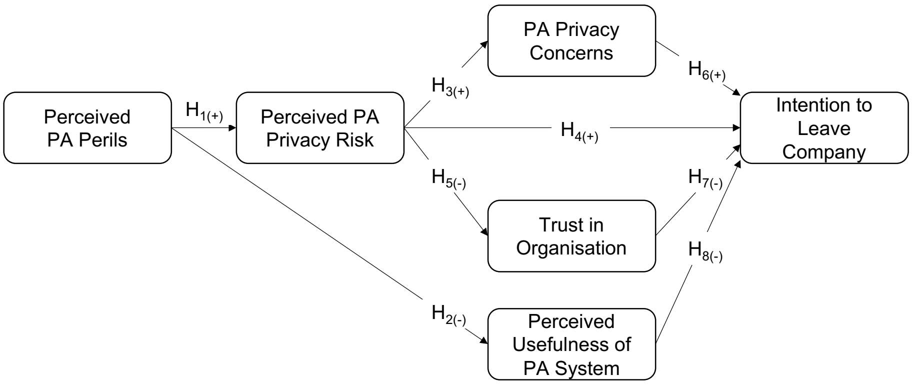

Figure 1. Research model.

4 Method

We evaluate our research model by conducting a scenario-based online survey implemented in oTree (Chen, Schonger and Wickens, 2016). In the scenario, participants take the role of employees who are confronted with the situation that their employer has decided to implement a PA system, which analyses their behaviour on the work computer. Following the introduction page, all participants are introduced to the PA system by means of multiple screenshots showing, first, views for individual employees without leadership responsibility and, second, views that are only available to team leaders. Figure 2 shows two exemplary screenshots. To create an immersive scenario, we align all graphical and textual stimulus material close to the available content on the websites of popular PA system companies (e.g., Microsoft Viva, SAP SuccessFactors). Thereby, we ensure that we only show participants content that is also available in existing PA systems. While the views for individual employees without leadership responsibility show analysis of their own work behaviour and well-being, the team leader views show evaluations of productivity at team level. Subsequently, participants enter the survey to answer a fully randomised survey incorporating the measurement scales of our research model.

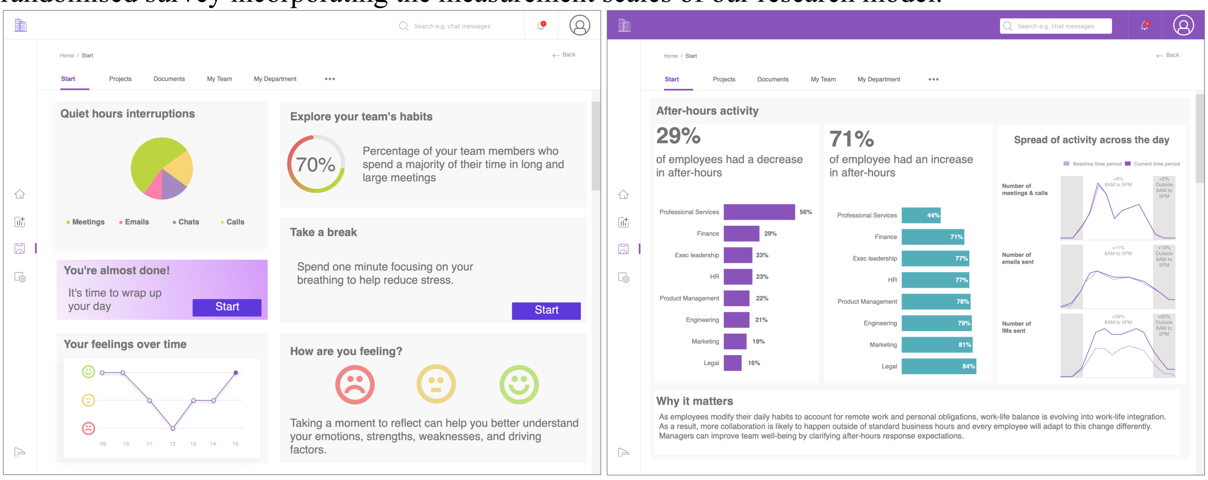

Figure 2. Exemplary PA system stimulus material including employee view (left) and team lead view (right).

Measures—whenever possible, we adapt the measurement instruments to the context of our study falling back on established and validated scales from literature. We adapt perceived PA privacy risk (PR) and PA privacy concerns (PAPRC) from Dinev and Hart (2006), Trust in Organisation (TRO) from Gabarro and Athos (1976), perceived usefulness (PU) from Venkatesh (2003) and intention to leave company (ITLC) from Cammann (1983). We conceptualize perceived PA perils as a formative construct based on Giermindl et al.'s (2021) extensive review and categorization of PA system perils. Following

MacKenzie et al.'s (2011) guidelines for item generation, we create a separate item for each of the six perils identified by Giermindl et al. (2021). We measure all items on 7-point Likert scales. Table 3 lists our adapted measurement instruments. Further, we collect demographic and trait information, including gender, age, knowledge of PA, individual privacy disposition (Xu, Dinev, Smith and Hart, 2011), risk propensity (Dohmen et al., 2011), current team leading role, and if participants currently work in an HR department.

Procedure and sample—we recruit participants using the German part of the Bilendi online market research panel. In this panel, participants initially sign up voluntarily and receive invitations to participate in (online) surveys and experiments. The chosen panel consists of adult individuals living and working in Germany. We incentivize participants with monetary rewards for participation, and they spent, on average, 12.4 minutes (SD=4.76) in the entire survey. Of the 551 initial participants, 338 finished with passing all attention and comprehension checks. With this final sample size, we fulfil the required threshold for detecting small-sized effects with a power of .80 and an alpha of .01 (Cohen, 1992). Within the sample, 54.7% are female, and the average (median) age is 44.3 (44) – ranging from 18 to 61 years. A risk propensity mean of 4.32 (SD=2.45; 11-point Likert scale ranging from 0: not at all willing, to 10: very willing to take risks; Dohmen et al. 2011) indicates that our sample is, on average, slightly tending to avoid risks. Participants' privacy disposition shows a mean of 5.21 (SD=1.22). About half of participants (51.5%) state to know what "People Analytics" means. 70.1% of the sample works at least less than half of their working hours from home, 32.0% state they currently pursue a team lead role and 14.5% state they work in an HR department.

5 Results

Measurement model—next, we use partial least squares structural equation modelling (PLS-SEM) to analyse our research model. We choose PLS-SEM due to both the exploratory character of our research endeavour and due to the inclusion of formative scales. We guide the process of model analysation and interpretation towards the established recommendations of (Hair, Hult, Ringle and Sarstedt, 2021). Following their guidelines, we start with measurement model evaluation. For all reflect constructs, we establish internal consistency reliability by confirming both compositive reliability (CR) and Cronbach's α values above the .70 threshold. We confirm convergent validity, as all Average Variance Extracted (AVE) value exceeds the threshold of .50. However, one item (TRO2) shows an outer loading below the typical cut-off value of .70. Following Hair and colleagues (2021), we evaluate whether excluding this item would cause reaching threshold values for AVE and internal consistency reliability. As those thresholds were already fulfilled before, we decide to not exclude this item. Next, we assess discriminant validity and confirm the Fornell-Larcker criterion (Fornell and Larcker, 1981) as well as the Heterotrait-Monotrait Ratio criterion for all reflective constructs. We summarise all measurement scales in Table 1. To analyse the remaining formative construct (PPA), we check the variance inflation factor (VIF), assessing collinearity issues in the measurement model. All VIF values are below the threshold of 5. However, assessing indicator relevance and significance led us to the decision to drop PPA3 as both its outer weight and loading are below .50 and negative. Last, we control for collinearity issues on construct level. VIF values above .20 and below 5.0 indicate that the structural model does not suffer from collinearity issues.

						Correlations				
Construct	**Mean**	**SD**	**CR**	**Cron. α**	**AVE**	**PR**	**PAPRC**	**PU**	**TRO**	**ITLC**
PPA	5.08	1.01	/	/	/					
PR	4.85	1.56	.929	.911	.722	.888				
PAPRC	5.46	1.40	.886	.883	.742	.661	.861			
PU	3.39	1.54	.906	.871	.722	-.450	-.597	.850		
TRO	3.73	1.37	.915	.904	.636	-.450	-.729	.785	.798	
ITLC	4.57	1.74	.917	.915	.856	.492	.650	-.516	-.711	.925

Table 1. *Construct descriptives, reliability measures, and correlations.*

Structural model—we evaluate our model employing bias-corrected and accelerated bootstrapping with 5000 subsamples, no sign changes and two-tailed testing. Figure 3 depicts the resulting path coefficients. As hypothesised, a higher level of perceived PA perils has a positive influence on perceived PA privacy risks (H_1) and a negative influence on perceived usefulness of PA system (H_2). Further, as hypothesised, perceived PA privacy risk shows a positive influence on PA privacy concerns (H_3) and a negative influence on trust in organisation (H_5). However, we find no evidence for a significant direct effect on intention to leave company (H_4; $p = .687$). Next, we find support for H_6 and H_7 – while PA privacy concerns positively influence intention to leave company, the influence of trust in organisation is negative. Last, we find no support for H8. There is no significant influence of perceived usefulness of PA system on intention to leave company ($p = .154$). Overall, our model explains 56.1% of the variance in intention to leave company (adjusted R^2). Following the effect size classification of Cohen (1988), we observe two small-sized effects (H_1: perceived PA perils on perceived PA privacy risk, H_6: PA privacy concerns on intention to leave company), two medium-sized (H_2: perceived PA perils on perceived usefulness of PA system, H_7: trust in organisation on intention to leave company), and two large-sized effects (H_3: perceived PA privacy risk on PA privacy concerns, H_5: perceived PA privacy risk on trust in organisation). Table 2 lists the effect sizes of all significant paths.

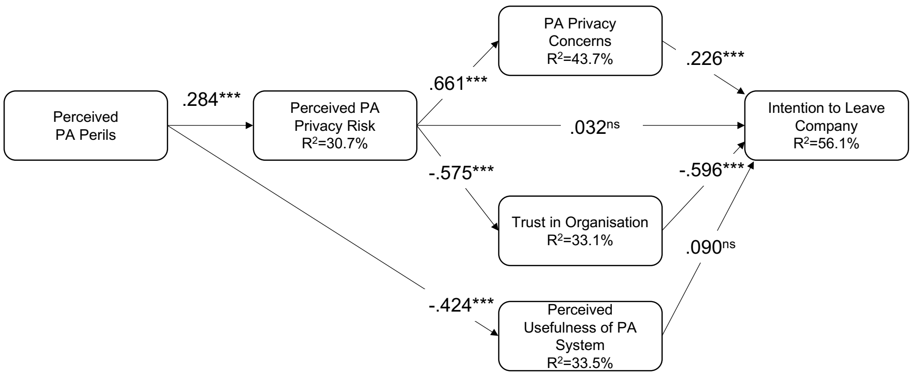

Figure 3. *Results of structural model testing. *** p < .001; ** p < .01; * p < .05.*

Independent Construct		**Dependent Construct**	**Coef.**	**f²**	**Effect Size**
Perceived PA perils	→	Perceived PA privacy risk	.284	.091	Small
Perceived PA perils	→	Perceived usefulness of PA system	-.424	.263	Medium
Perceived PA privacy risk	→	PA privacy concerns	.661	.778	Large
Perceived PA privacy risk	→	Trust in organisation	-.575	.494	Large
PA privacy concerns	→	Intention to leave company	.226	.061	Small
Trust in organisation	→	Intention to leave company	-.596	.219	Medium

Table 2. *Effect size classification for found effects following Cohen* (1988).

Control variables—next, we assess the potential influence of secondary variables. Controlling for demographic and trait information yields six significant effects. First, participants' overall disposition to privacy shows a positive effect on perceived PA privacy risk ($\beta = .362$, $p < .001$). Second, participants' risk propensity positively influences both perceived usefulness of PA system ($\beta = .247$, $p < .001$) and intention to leave company ($\beta = .112$, $p < .01$). Third, we find participants' age negatively influences perceived usefulness of PA system ($\beta = -.161$, $p < .001$). In contrast, working in an HR department shows a positive effect on perceived usefulness of PA system ($\beta = .449$, $p < .01$). None of the control variables alters any of the hypothesised main effects in terms of magnitude, sign, or significance.

PA maturity levels—in addition to controlling for demographic and trait information, we also assess the robustness of our results in light of different PA system maturity levels. Giermindl and colleagues (2021) outline PA systems can differ depending on the implemented and activated analytic capabilities, particularly in terms of the perils they pose. To examine whether these maturity levels affect employee perceptions, we compare three subgroups of our subjects. Using experimental treatment manipulation, we assign each participant randomly to see one of three majority levels (between-subjects design): descriptive, predictive, or prescriptive. Following the definition of Giermindl et al. (2021), in the descriptive treatment (n=111), the PA system only provides aggregated analyses of past data. In the predictive treatment (n=115), the PA system provides for each analysis an additional statement forecasting future development below each analysis (e.g., "the number of after-hours team activities is currently expected to increase by 12%"). Last, in the prescriptive treatment (n=112), the PA system provides both the predictive statement and additionally recommends "decisions and courses of action, based on an analysis of past data and alternative, future scenarios" (Giermindl et al., 2021, p. 416) (e.g., "cancel at least two of the meetings next week to avoid a major increase in team after-hours activities"). To ensure that participants perceive our externally manipulated treatment conditions, we included one manipulation check question in our survey (among the questions of the main survey). Specifically, we ask participants to state their agreement with the statement "The system provides direct forecasts and predictions of future developments." Following our conceptualisation, we expect to find measurable differences between those groups in answering this item, as the respective PA maturity levels each provide different analytical capabilities and, therefore, different features (e.g., providing predictions on future events or providing recommendations on how to impact the likelihood of future events happening). And indeed, using ANOVA ($F_{(2,355)} = 6.00, p < 0.01$) and post-hoc TukeyHSD analysis, we can confirm a significant difference between descriptive and predictive treatment ($D_{pred\text{-}desc} = .535, p < .05$), and between descriptive and prescriptive treatment ($D_{pres\text{-}desc} = .584, p < .01$), but not between predictive and prescriptive treatment ($D_{pres\text{-}pred} = .049, p = .963$). We conclude that our manipulation is partly successful. As depicted in Figure 4 however, controlling for differences on construct level across treatments, we find no significant difference, indicating that our results are not sensitive to the level of PA maturity.

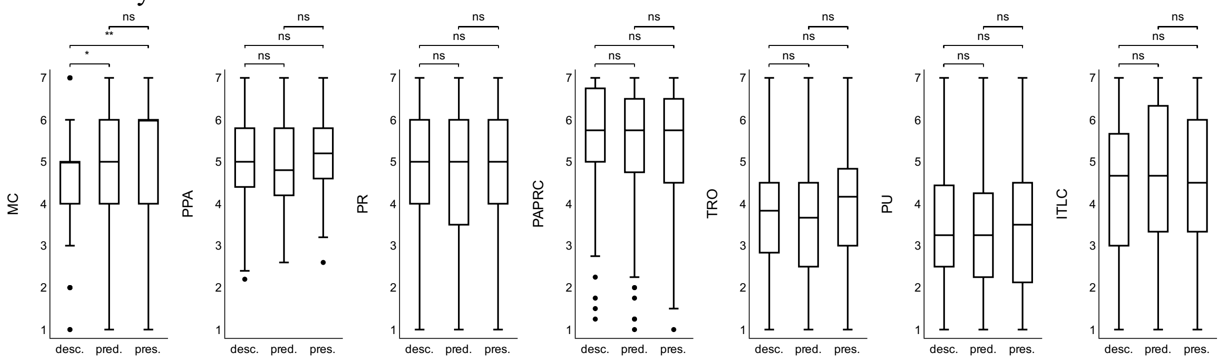

*Figure 4. ANOVA for treatment effects. ***: <.001, **: <.01, *: <.05.*

6 Discussion

Theoretical implications—to the best of our knowledge, our study is the first to provide empirical evidence on employees' perceptions of PA systems. While previous research mainly approaches the subject of PA from a purely technology-centred and often only theoretically discursive perspective, our study provides the first quantitative evidence on employee perception of PA systems. Earlier studies on aspects of algorithmic human resource management provide valuable information on their respective topics, such as perceived fairness in algorithmic decision-making or applicants' perceptions of hiring algorithms (Lee, 2018; Kaibel et al., 2019). However, by extending and adopting the theoretical lens of privacy calculus by Dinev and Hart (2006) to the context of employee perception of PA system implementation at their workplace, we provide the first theoretically founded explanation for investigating PA perception. We extend the body of knowledge on the implications of the currently growing trend to meticulously track employees' behaviour at work. In this, we further provide first insights into how the perception of Giermindl et al.'s (2021) six PA perils can be assessed by means of a formative survey construct and as an antecedent of both perceived risk of PA and the perceived usefulness of PA. Our research model has proven to be robust throughout the performed study. In this regard, controlling for different PA system maturity levels did not alter any of the surveyed dimensions significantly, indicating no overall different perception of the PA system. This is particularly interesting, as it indicates that even the most basic levels of PA maturity already affected employees already form strong and robust opinions about the PA systems. Furthermore, we find that the risks associated with the PA system do not directly influence employees in their intention whether to leave their company. Moreover, the effects appear to be mediated via both the resulting PA privacy concerns as well as reduced levels of trust in the organisation. Thereby, our study emphasises the strong association between PA implementation and the so far not considered impact on employees' trust in the company implementing it. This aspect is relevant in so far, as we cannot observe a mitigating effect of PA system's perceived usefulness on employees' intention to leave the company. Next, our study provides insights into employee-specific differences in assessing PA systems at their workplace. It appears that employees working in HR evaluate the risks of PA systems as less severe and put higher confidence in the perceived usefulness of the systems. This finding is in line with reports from prior literature describing HR departments as overly confident about the benefits arising from PA usage and less inclined to challenge system-generated recommendations, which is outlined as ample risks for employees (Giermindl et al., 2021; Klöpper and Köhne, 2022; Tursunbayeva et al., 2022).

Practical implications—our study also provides practical implications for PA developers, organisations, and regulators. First, in comparison to other employees, those who work in HR rate the overall usefulness of PA systems higher. However, it has been noted that HR practitioners lack a certain level of data literacy, which can lead them to engage with biased or erroneous data without recognising it as such (Shet et al., 2021). The enthusiasm of HR personnel towards PA might hinder them from acknowledging the full scale of risks posed by PA, which can have drastic consequences for employees, such as discrimination based on biased sets of data. Hence, during the adoption process of PA, it might be wise to include (external) experts on the matter and to pay more attention towards the concerns of employees. As HR staff also represent the explicit target group for advertising PA systems (Microsoft, 2022) frequently with a misleading employee-centric narrative of their systems, specific training on the statistical methods used and on the interpretation of their results could contribute to a more reflected attitude towards PA systems. Literature connects different maturity levels of PA with different levels of risks for employees (Giermindl et al., 2021; Adams-Prassl, 2022) – an aspect that is also taken into account when it comes to regulating PA systems. The EU's proposed Act on Artificial Intelligence (AI), for instance, classifies algorithm- or AI-driven personnel management tools as high-risk applications in terms of data privacy and potential discrimination (Adams-Prassl, 2022; European Commission, 2022). Nevertheless, employees already perceive the very basic levels of PA (i.e., descriptive PA) as posing the same level of perils and perceived risks as the more advanced and sophisticated maturity levels of PA (i.e., predictive and prescriptive), leading them to the similar levels of intention to leave their company. In this regard, it is not sufficient if research discusses the varying risks from a technical and organisational perspective, as employees do not recognise these differences at all. It may also be that the most basic stages of PA system maturity already face such pronounced rejection among employees that a ceiling effect sets in here. Managers and employers, in general, may underestimate the full-scale implications of PA implementation in the workplace and may want to re-evaluate this step. As our results suggest, no matter how useful the PA system is perceived to be, this usefulness cannot mitigate the levels of trust erosion and privacy concerns it causes. Consequently, organisations should not thoughtlessly rush to implement a PA system driven by the currently increasing need to decentralise work (remote work). Instead, they should seek careful and open communication and consultation with their employees and encourage their active participation in deciding whether to implement a PA system and how it will be used. At the same time, PA developers should proactively address existing employee concerns and apprehensions. Approaches from the field of data record anonymisation and pseudonymisation could help to reduce data privacy risks and concerns. Although this should render some directly individual-related analyses no longer possible, the majority of analyses should not require direct reference to individuals and could be obtained with only aggregated data. A voluntary commitment by PA developers for explicit data economy or, for instance, the implementation of a differential privacy approach (Wood et al., 2018) could provide additional leverage in this regard. Even though they have a vested interest in presenting their system as analytically powerful, the manifold analytic capabilities could ultimately backfire if their customers see employee trust relationships erode and turnover rates increase. Last, our results inform legislative regulators. At a certain level, legislative approaches towards this already exist, for instance, in Germany. Works councils there have a strong right of co-determination in the use of AI-based applications: the Works Council Modernisation Act, which was passed at the beginning of 2021, explicitly addresses the inclusion of external experts to clarify uncertainty about existing risks in advance (Bundesministerium für Arbeit und Soziales, 2021; Klöpper and Köhne, 2022). However, this constitutes a relatively specific approach that only works on the premise that an organisation has a works council. This, by far, is not always the case. Employees in organisations without co-determination should have the same level of legislative protection. Overall, it should not be the responsibility of the workers' council, who are, at last, employees themselves, to prevent the implementation of potentially harmful approaches towards people management.

Limitations and future work—as any study, this study's findings are subject to limitations. First, participants' actual perception of a PA system and their ultimate intention to leave their company may vary from what they state within a (monetary incentivised) scenario-based survey. Observational studies and field experiments represent natural complements of our first empirical evidence. However, we are confident that our stimulus material created an immersive and realistic scenario, as we closely aligned it to existing PA systems. Next, in terms of sample, the generalisability of our results is subject to the limitation of an entirely German sample. Broader studies with more diverse countries of origin are undoubtedly a natural next step. As PA originates from the US-American market, consequently, a vast number of studies specifically address the specific traits of those systems (Klöpper and Köhne, 2022). However, EU legislation prevents some of the invasive features from being applied. Thus, European-centred studies looking at PA are a valuable addition to the current body of literature. Furthermore, there appears to be further potential in capturing perceived PA Perils as a formative survey construct. Assessing how to capture the aspect of eminent path dependencies due to PA systems as a survey item seems necessary. Nevertheless, our results show that our existing approach to grasping the perceived PA perils construct already captures a substantial proportion.

7 Conclusion

PA is a highly debated topic among researchers and practitioners and has gained substantial momentum as organisations are searching for solutions that support the managing of dispersed teams in new, increasingly decentralised working environments caused by the COVID-19 pandemic. Even with employees returning to the traditional office spaces, PA will stay. However, the current discourse on PA overlooks the perspective of the employees. While the risks for employees are increasingly addressed from a theoretical or mere technical perspective, there is an evident lack of empirical results. We demonstrate that employees can value the associated privacy risks brought by PA deployment can ultimately cause them to consider leaving their company. While the literature discusses whether these different levels pose different risks and the legislature also pays attention to these differences when regulating systems, the reality for employees is different. It makes no difference to employees which maturity level PA systems achieve. Therefore, it is questionable whether the current use of the systems is at all in the interests of the employees or whether this places an additional burden on them, which, in the long term, leads to a deterioration in productivity and satisfaction at work and, in the worst case, can also lead to mental and physical problems due to additional stress. If we want to exploit the potential of these systems, we need to pay more attention to the employees' perspective in our research and PA system development. IS research has sufficiently strong theories and experience to examine systems from a user-oriented and, thus, human-centred perspective. We should put these skills to use.

Appendix

Construct	Code	Item (adapted)	Loading / Weight
Perceived PA Privacy Risk (reflective) (Dinev and Hart, 2006)	PR1	How high do you think the risk is for employees that… records of workplace behaviour are passed on to third parties?	.906
	PR2	…personal data will be misused?	.897
	PR3	…personal data is passed on to other parties or companies without the employees' knowledge?	.923
	PR4	…personal data could be passed on to government authorities?	.821
PA Privacy Concerns (reflective) (Dinev and Hart, 2006)	PAPRC1	I am concerned that the information I submit to the system may be misused.	.887
	PAPRC2	I am concerned that a person may find private information about me in the system.	.801
	PAPRC3	I am concerned about submitting information to the system because I do not know what others can do with it.	.870
	PAPRC4	I have concerns about submitting information to the system because it could be used in ways I did not anticipate.	.885
Perceived Usefulness (reflective) (Venkatesh et al., 2003)	PU1	I would find the system useful in my everyday work.	.896
	PU2	Using the system would help me complete tasks faster.	.896
	PU3	Using the system would help me increase my productivity.	.884
	PU4	Using the system would increase my chances of getting a raise.	.708
Trust in Organisation (reflective) (Gabarro and Athos, 1976)	TRO1	I believe that this employer has a high level of integrity.	.815
	TRO2	I can assume that this employer will treat me consistently and predictably.	.652
	TRO3	This employer is not always sincere and honest. (reversed)	.765
	TRO4	Generally, I believe this employer has good intentions and motives.	.863
	TRO5	I do not believe this employer treats me fairly. (reversed)	.811
	TRO6	This employer is open and honest with me.	.872
	TRO7	I am not sure if I trust this employer completely. (reversed)	.784
Intention to leave Company (reflective) (Cammann, 1983)	ITLC1	Given this situation, it is likely that I will actively look for a new job in the next year.	.927
	ITLC2	Given this situation, I will often think about quitting.	.902
	ITLC3	Given this situation, it is likely that I will look for a new job in the next year.	.946
Perceived PA Perils (formative) (Giermindl et al., 2021)	PPA1	The system can marginalize human thinking and erode the managerial competence.	.261
	PPA2	The system can reduce employee autonomy.	.462
	PPA3	The system can foster path dependencies. This means focusing on actions that have proven successful in the past while ignoring new patterns and parameters.	-.373†
	PPA4	For leaders, the system can lead to reductionism and an illusion of control.	.336
	PPA5	The analyses created by the system can lead to self-fulfilling prophecies. Whether the prediction was correct or merely came true as a result of the reaction to the analysis cannot be determined.	.047
	PPA6	The system can compromise transparency and accountability.	.268

Table 3. Measurement instruments. † denotes items removed during model evaluation.

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