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Artificial Intelligence and People Analytics in Human Resource Decision-Making: Opportunities, Challenges, and Ethical Imperatives

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Abstract: A new era for human resources is beginning, driven by the use of artificial intelligence (AI) and people analytics to inform human resources (HR) decisions. This report presents an integrated, multi-disciplinary review of the current state-of-the-art of using AI and people analytics in HR, based upon established theoretical models from information systems, organizational behavior, ethics, etc. The report describes how traditional descriptive HR metrics have evolved to predictive and prescriptive HR analytics through the application of machine learning, natural language processing and algorithmic decision systems. In addition to providing examples of AI/people analytics applications throughout recruitment, performance management, retention, workforce planning and employee wellbeing, the report also assesses both the positive impacts of AI/people analytics to enable HR decisions to be made more quickly, efficiently and strategically; as well as the significant negative implications of adopting these technologies - i.e. Algorithmic bias, erosion of employee privacy, distrust of employees toward HR systems, deskilling of HR professionals. Additionally, this report reviews ethical and legal frameworks related to fairness, accountability, transparency and the General Data Protection Regulation. Based on a synthesis of recent empirical and conceptual scholarship (2015 – 2025), the report argues that although AI and people analytics represent unparalleled opportunities for enhancing the quality and effectiveness of HR decisions; un-critically adopting them will lead to institutionalized biases, diminished employee dignity and degradation of the relational core of human resource management. Therefore, the report advocates for a human-centered augmented intelligence approach to HR where ethical principles are embedded within system design and human discretion is preserved. Finally, the report outlines a forward-looking research agenda centered around explainable AI, algorithmic literacy among HR professionals and co-design of analytics systems by employees.

Keywords: *artificial intelligence, people analytics, HR analytics, algorithmic decision making, human resource management, ethics, bias, workforce analytics.*

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Introduction

Human resource management (HRM) is currently experiencing a technological revolution. The confluence of big data, cloud computing and advanced machine learning algorithms has led to the emergence of "people analytics" which refers to the systematic identification, quantification and analysis of workforce data in order to improve business results; and artificial intelligence in HR (Marler & Boudreau, 2017; Tambe, Cappelli & yakubovich, 2019). Today companies across industries are implementing AI-enabled platforms to identify resumes for job openings; forecast when employees will leave; Tailor training programs to each individual's learning needs; analyze employee sentiment from survey responses; and collect passive data regarding employee productivity (van den Broek et al., 2021; giermindl et al., 2022). The allure is great: data-based HR decisions made faster, less subjectively and with greater strategic alignment than before.

However, there exists considerable controversy surrounding this technological transformation. As recently documented by critical scholars, algorithms can perpetuate and exacerbate long-standing prejudices; diminish employee privacy; and dehumanize individuals through their quantification (Hunkenschroer & Kriebitz, 2023; Köchling & Wehner, 2020). Perhaps most notably illustrated was the failure experienced by amazon whose AI recruiting tool systematically undervalued qualified female applicants (Dastin, 2018). Although AI has been heralded as capable of reducing human prejudice by automating hiring processes, the potential exists for AI to embed prejudice on a much larger scale. Moreover, because so many machine learning models operate in a black box environment raising serious concerns regarding procedural justice; accountability; and fairness in making employment-related decisions (Cheng & Hackett, 2021) Research on AI and people analytics has grown significantly over time; however research has largely occurred in silos across various fields such as computer science; management; ethics; law; industrial/organizational psychology. This paper integrates the expanding field of study to answer three interrelated questions: (1) how are AI and people analytics changing the way HR makes decisions across key domains? (2) what are the primary benefits and risks of using these technologies? (3) what theoretical models can guide the responsible use of AI in HR?

This review paper covers peer reviewed journal articles; book chapters and conference proceedings from reputable sources that were published between January 1st 2015 and January 31st 2025. The purpose of this review article is to synthesize scholarly work across multiple disciplines; thus creating a balanced critique of both the advantages and disadvantages of using AI in HR. In addition to examining applications of AI/people analytics in HR across several domains (section 4); this report reviews theoretical models applicable to understanding AI/people analytics (Section 3); strategic impacts of AI/people analytics (Section 5); challenges/risks associated with AI/people analytics (section 6); ethical/legal issues surrounding AI/people analytics (section 7); and future directions for research on AI/people analytics (Section 8).

Evolution and Definition of AI and People Analytics in HR

From Personnel to Predictive Models

In addition to being supported by a rich history of intellectual and practical development, the origins of people analytics are rooted in the systematic tracking of employee data by personnel departments beginning in the early twentieth century (Cascio & Boudreau, 2012). Although HR reports have been developed using descriptive statistics for many years, HR information systems (HRIS) were first developed during the 1980s-1990s which allowed for more detailed data tracking, yet most decisions were still made with little quantitative support and largely through intuition/experience (Angrave et al., 2016). The phrase “workforce analytics” emerged as a concept around the year 2000. It was the combination of "big data" and "advanced analytics" in the 2010s that really changed the landscape of what is possible today in the area of people analytics. A comprehensive review of the current state of human resource analytics was published by Marler and Boudreau (2017) where they found that human resource analytics has transitioned from a peripheral technical function to a strategic function. They found that there continues to be a large disconnect between the potential benefits of applying data analysis to human resources and how often these tools actually positively affect business decisions. This disconnect, according to Marler and Boudreau (2017), is due to poor quality of the data used in these analyses, limited analytical ability within HR departments, and a cultural environment that resists making informed decisions based on empirical research.

Definition of People Analytics and AI in HR

For the purposes of developing clear concepts, differentiating among closely-related terms is important. People analytics (also referred to as HR analytics) can be generally described as the application of various types of analytical approaches i.e., statistical models, data mining, machine learning to workplace data to improve both individual employee performance and overall organizational performance (Tursunbayeva, Di Lauro, & Pagliari, 2018). Descriptive analytics answers questions such as “what happened?” while diagnostic analytics attempts to answer the question “why did that happen?” Predictive analytics addresses the question “what will happen next?” Prescriptive analytics asks “what should I do about it?” AI in HR is an application of people analytics that uses AI technologies to either replace or enhance existing HR functions (Tambe et al., 2019). While AI is not simply another tool that extends previous statistical techniques, it does provide the ability for computers to learn autonomously from large amounts of data, identify patterns across vast amounts of data and generate new insights from data that have never before been analyzed. In their work, Cheng and Hackett (2021) distinguish between rule-based algorithms such as Boolean searches in applicant databases and learning algorithms i.e., Neural Networks that predict a candidate’s likelihood of taking flight based upon several hundred candidate attributes. According to Cheng and Hackett (2021), rule-based algorithms present relatively few problems relative to learning algorithms regarding transparency and fairness.

The Current State of Adoption

People analytics and artificial intelligence (AI) have recently become part of many HR professionals' toolkit as evidenced by a recent study that stated that 69 percent of organizations surveyed globally indicated that their investments in people analytics grew during the last two years with a little more than one-quarter of those surveyed indicating that their organization's investments were increasing in both predictive and prescriptive analytics (Giermindl et al., 2022). The growth has been fastest in larger tech and financial services firms. Smaller organizations along with government entities have been slower to adopt these tools. The rapid increase in remote work due to the COVID-19 pandemic is accelerating the need for organizations to develop the ability to monitor remote worker productivity and well-being, creating new opportunities for using analytics to measure remote workers' performance (Bélanger & Morselli, 2022).

Since the emergence of the first Human Resource Information System (HRIS) in the late 1980s, HR managers have increasingly used quantitative approaches to understand the characteristics of employees and how they contribute to the success of organizations. Early HRIS systems allowed HR managers to create reports that provided them with basic information such as headcount, turnover rate and cost per hire. While these early systems facilitated more efficient collection and analysis of data, the decision making process continued to rely heavily on past experience and intuition (Angrave et al., 2016).

Theoretical Foundation

Evidence-Based Management and the Resource-Based View

As the amount of data collected by employers continues to grow, so too does the complexity of analyzing this data. To support this increasing complexity, researchers are developing and testing new theories to explain why some organizations are able to successfully use data-driven decision making more effectively than others. One theory that has been developed specifically to address this issue is called evidence-based management (EBM). EBM suggests that managers make better decisions if their decisions are made using data supported by research rather than relying on "best practices," trends or gut instincts. Therefore, evidence-based management would suggest that the development of people analytics would provide an important opportunity for HR managers to use data-supported approaches to managing employees. Another theory that provides additional justification for developing and using people analytics is called the resource-based view (RBV) of the firm. RBV is a microeconomic framework that views the firm as a set of unique resources including human capital. The RBV suggests that the key to achieving sustainable competitive advantages is to accumulate and leverage rare, difficult-to-duplicate resources. Since human capital represents one type of resource that can help achieve sustainable competitive advantages, the development of people analytics could provide HR managers with ways to analyze and identify the characteristics of high performing employees and apply that knowledge to attract and retain employees who possess similar characteristics. Therefore, evidence-based management and the resource-based view of the firm provide strong theoretical foundations for continuing to invest in and expand the use of people analytics.

The above passage contains three sections that is Sociomateriality and Affordance Theory, Ethical Theories and Algorithmic Fairness, and finally, Trust and Technology Acceptance. These sections cover important theoretical and practical considerations when deploying AI and people analytics tools within Human Resource (HR) departments.

Sociomateriality and Affordance Theory

Sociomateriality takes a more critical view of AI in HR and suggests that organizations should look at both the "technical" aspects of an algorithmic tool, and how HR practitioners interpret those results in terms of their own professional experiences, the organizational politics around the collection and interpretation of employee data, and the response of employees to those interpretations. Similarly, affordance theory recognizes that technology has the potential to offer a variety of options for user action (affordances), but that the realization of those actions depend on the specific context in which users act. For instance, the same attrition-prediction model used to predict who is likely to leave an organization may support proactive retention discussions in one company, but encourage punitive disciplinary action in another.

Ethical Theories and Algorithmic Fairness

As AI becomes an increasing part of HR's decision making, including determining who gets hired, fired, or promoted, there is a need for organizations to apply explicit ethical theories to determine what is acceptable behavior. A utilitarian ethic could argue that the use of algorithmic decision-making would lead to greater good for all employees in the organization. On the other hand, deontological ethics emphasize respect for humanity and human rights, and therefore raise questions regarding treating employees as mere data points. Finally, Sen's Capabilities Approach (Sen, 1999) focuses on expanding or contracting an individual's substantive freedom to achieve well-being. In the area of Computer Science, researchers have developed a new field called Algorithmic Fairness (AF), where researchers distinguish between multiple statistical definitions of fairness such as Demographic Parity, Equalized Odds, and Individual Fairness that are often mutually exclusive (Barocas et al., 2019). Köchling and Wehner (2020) conducted a systematic review of AF definitions related to personnel selection and concluded that none of the definitions are universally applicable and that organizations will always have to make trade-off decisions based on the organizational context.

Trust and Technology Acceptance

The Technology Acceptance Model (TAM) and subsequent TAM-related research models have been successful in developing a micro-level framework for explaining why employees and HR practitioners accept or reject analytics-driven systems. While TAM explains that perceived usability and perceived ease-of-use are the two most significant factors in predicting employee/HR practitioner adoption of analytics-based systems, recent revisions to TAM include trust in the reliability, transparency, and fairness of the algorithm as additional factors influencing acceptance (Lee & See, 2004; Shin, 2021). As long as employees perceive that an AI system is evaluating them according to standards they don't comprehend nor can influence, then trust drops dramatically, and so does acceptance, even though the system itself is functionally correct.

Applications of AI and People Analytics in HR Decision Making

Recruitment and Selection

Recruitment and selection is currently the most widely accepted application domain for AI in HR. Many firms today utilize natural language processing (NLP) to extract relevant information from resumes, sentiment analysis to analyze applicant responses during video interviews, and various types of predictive models to assess a candidate's likelihood of succeeding in a particular position (Campbell et al., 2020). Additionally, gamified assessments and AI-scored situational judgment tests are becoming increasingly popular. Proponents of AI-based recruitment processes argue that large numbers of candidates can be reviewed more quickly and objectively by algorithms than by human recruiters (Hunkenschroer & Kriebitz, 2023).

However, empirical evidence reveals that the situation is far from clear-cut. Tambe et al. (2019) warn that hiring algorithms designed to select candidates using historical data will often produce hiring patterns that reflect existing workforce demographics; in effect, they will intentionally discriminate against underrepresented groups. A well-documented example is Amazon's faied attempt at developing an experimental resume-screening tool that evaluated candidates' suitability for positions based on certain keywords in their resumes. After Amazon discovered that the tool downgraded resumes that included words like 'women', it was discontinued (Dastin, 2018). Van den Broek et al. (2021) studied the development of an AI hiring tool through ethnography. Their findings indicate that converting expert recruiters' implicit knowledge into formalized algorithms is far from straightforward. In fact, as shown in their study, the tool developed often reflected the biases present among developers and also those of the organization. Furthermore, Cheng and Hackett (2021) point out that selecting applicants for jobs utilizing AI is particularly hazardous since many job-performance criteria themselves are subjective and historically biased. Therefore, they recommend combining AI screening with human assessment - i.e. augmentative versus automative approaches.

Performance Management

AI is helping to shift performance management away from traditional one-time evaluations to a continuous flow of feedback. Natural Language Processing (NLP) Tools help review the data collected in emails and calendars to provide "objectively" defined measures of how collaborative, responsive and focused employees are (Chamorro-Premuzic & Akhtar, 2019). In addition to providing feedback, there are many examples of companies using AI to send nudges to employees for real time performance improvements, or to identify potential underperformers so they can receive interventions. While it's hoped that this will make it easier for managers to evaluate employees objectively, and avoid the recency bias and subjectivity found in more traditional methods, many critics say otherwise.

While there are many positive uses of people analytics, there are also many dark side issues. As noted by Giermindl et al. (2022), while people analytics should ideally be used to improve decision making, it can instead be used as a tool for controlling behavior. Continuous monitoring of employee performance can create a panopticon like environment that creates increased levels of stress and decreases intrinsic motivation. The passive collection of employee data (e.g., tracking keystrokes, mouse movements, etc.) raises serious questions regarding privacy rights and the dignity of employees. Additionally, as previously mentioned, the definition of performance is typically limited to whatever is being measured by the algorithm. For example, a sales person could optimize their behavior for whatever metric is being evaluated, rather than developing meaningful long term relationships with customers. Research by Kallio et al. (2020), in the educational context, and research by Giermindl et al. (2022) in general business, demonstrate that performance metrics can result in decoupling surface level compliance without actual improvement when employees believe that they are being monitored.

Employee Retention/Attrition

The application of predictive models of voluntary turnover is arguably the most prevalent form of people analytics. By evaluating attributes such as tenure, salary, distance from home, engagement survey responses, email metadata and other relevant criteria; algorithms determine a "flight risk" measure for every employee (Bersin, 2018). Using this metric, Human Resources can develop specific retention strategies for at-risk employees. IBM is an example of a company utilizing an AI-based predictive attrition model which was reportedly successful in predicting 95% of employees' flight risks thereby enabling managers to take proactive steps to retain those employees (Rosenbaum, 2019). Although the reported success rate of employee turnover prediction appears to be promising; several ethical dilemmas exist. Employees are assessed by their employer(s) without their explicit knowledge or consent which precludes them from disputing or correcting the data upon which managerial decisions are made. An additional concern exists relative to self-fulfilling prophesies. Once a manager determines that an employee is at risk of leaving, the manager may choose to invest less resources into developing that employee or possibly exclude him/her from important activities which will increase the likelihood of that employee exiting (Gal et al., 2017). Furthermore, as noted earlier, algorithms determining turnover predictions may include demographic characteristics (i.e., age, gender, marital/family status) resulting in implicit discrimination against certain groups (Hunkenschroer & Kriebitz, 2023). Due Process Issues arise because algorithms predict turnover but do not necessarily cause turnover.

Workforce Planning/Talent Development

AI allows for sophisticated forecasting models and demand-supply analyses for workforce planning and identifying gaps in required skills. The use of LinkedIn's AI-driven skills taxonomy enables mapping of individual competencies to emerging job roles within an organization thus enhancing internal mobility options (LinkedIn Talent Solutions, 2020). Organizations have begun implementing internal gig platforms where AI automatically assigns employees to short-term projects based on their profile and experience. This purportedly increases access to project opportunities for all employees and breaks down departmental barriers. Skills taxonomies are inherently socially constructed and reflect existing social hierarchies related to what are considered valuable skills (Cheng & Hackett, 2021). If left unmonitored, algorithms designed to match employees with jobs may actually perpetuate occupational segregation. Employees whose skills are not represented by the taxonomy - i.e., employees working in non-traditional work arrangements or with informal training - may be excluded from accessing future career opportunities.

Employee Engagement and Well-being

Using sentiment analysis of employee surveys, internal social media content, email communications and other similar digital communication sources enable organizations to track employees' emotional state in near-real time. Many organizations utilized AI-enabled platforms during the COVID-19 pandemic to assess remote workers' mental health through linguistic analysis (Belanger & Morselli, 2022). At first glance, these systems appear beneficial; however, numerous criticisms exist that describe these applications as "surveillance of emotions" that may normalize regular fluctuations in mood and expose sensitive personal information about remote workers to employers (Giermindl et al., 2022). Similar to previous statements, when employers utilize AI to determine an employee's mental state, the boundaries between caring for an employee's mental wellness and intruding upon that employee's mental wellness become increasingly blurred.

Benefits and Strategic Value

There are several types of benefits associated with using artificial intelligence (AI)-driven people analytics that will extend Human Resource's (HR) role from providing an administrative function to being a strategic business partner. Better Decision-Making and Faster Decisions. Because algorithms can evaluate and analyze so much more information than human decision-makers, there could be less opportunity for cognitive bias and quicker evidence-based decisions (Boudreau & Cascio, 2017). AI can reduce the time it takes to hire for large-scale hiring campaigns from weeks down to just days.

More Objective and Fairer (In Theory).

Proponents also claim that removing human subjective input from the beginning stages of the evaluation process, AI can help make companies more diverse demographically. Of course, this would have to happen if AI was created and evaluated fairly (Campbell et al., 2020).Structured, algorithmically-scored assessments tend to be more predictive of job performance than unstructured interviews.

More Personalized Learning Recommendations.

Like how Amazon or Netflix recommend products to customers based on their preferences, AI allows employers to provide each employee personalized learning recommendations, career paths and benefits recommendations.

A More Strategic View of Workforce Analytics.

Analyzing aggregated data provides insight into trends that may be invisible to local managers; for example, which departments generate the most new hires, what factors drive innovation, and where potential succession risks exist. With this type of strategic workforce analytics, HR has the ability to contribute to company-wide strategies in the same manner as finance and/or marketing do (Marler & Boudreau, 2017).

Reduced Costs and Increased Productivity.

Automating routine HR tasks (for example, scheduling interviews, answering policy questions via chatbots), allows HR professionals to focus on other "higher-value" aspects of HR. Using predictive attrition models reduces turnover related costs, which vary depending on the specific role (estimated at 20-200 percent of salary).

It should be understood that these benefits are not automatically realized. Whether or not the benefits are realized will depend on the quality of the underlying data, the skills of those analyzing the data, whether or not the data analysis is integrated into decision-making processes, and whether or not employees trust the system. As Angrave et al. (2016) predicted, due to HR's limited analytical capacity, and its history of being marginalized from the strategic data discussion, many organizations implement trendy AI tools but do not have either the foundation or culture to utilize them effectively.

Challenges and Risks

Algorithmic Bias and Discrimination

Algorithmic bias is perhaps the most studied challenge regarding people analytics. Bias can occur at any step along the way -- in defining the problem (What constitutes good performance?); in collecting data (Who gets measured?); during model development (Which characteristics get selected?); or after deployment (How are scores utilized?). Köchling and Wehner (2020) found 45 empirical studies demonstrating discrimination by algorithms used in personnel selection against individuals based on gender, race, age, and disability. They conducted a systematic review and discovered that algorithms trained on historical employment data frequently reproduce existing inequalities due to the fact that the data upon which they were developed reflects an inequitable world. Furthermore, even when sensitive features such as gender are eliminated from consideration in developing a model, proxy indicators such as name, zip code or career gaps permit discriminatory behavior (Barocas et al., 2019). While this is primarily a technical issue, Hunkenschroer and Kriebitz (2023) stated that from a human rights standpoint, AI recruitment violates an individual's rights to work, privacy and fair treatment if the technology is applied without sufficient protective mechanisms. They therefore advocate for obligatory human rights impact assessments prior to implementing high-risk HR algorithms. Tambe et al. (2019) also stressed that "debiasing" algorithms represents a wicked problem since fairness is a disputed concept: statistical fairness measures often clash with one another and selecting among multiple fairness measures requires making value laden tradeoffs.

Data Privacy and Security

Employee data required for people analytics is often obtained through passive means within an organization such as enterprise systems, emails, calendars and wearable devices. However, EU GDPR stipulates very strict conditions under which employee data may be processed including purposes limitations, data reduction and prohibiting employees from being subjected to purely automated decisions with significant consequences (Article 22). In practice many AI-based HR applications exist in a regulatory gray zone. Due to the significant imbalance in power between employers and employees few employees can provide true free consent for their data to be used. Additionally, the capture of "data exhaust," i.e., the generation of additional data resulting from digital activities while working, creates concerns about widespread monitoring that can suppress creative dialogue.

Employee Trust and Acceptance

Trust is an area where AI in HR has an Achilles' heel. Repeatedly, research has shown that employees are skeptical about algorithm-based decision making. Employees have been shown to be particularly distrustful of algorithm-based decision making in areas involving subjective judgments and/or high stakes decisions, i.e. hiring and evaluating performance (Lee, 2018; Newman, Fast, & Harmon, 2020). Employees tend to believe that humans make decisions based on qualitative characteristics of individuals more fairly than do algorithms. Employees are less likely to accept algorithm-based decisions as legitimate when they do not know how the decision was made (Shin, 2021). If trust is lost, then the benefits associated with using analytics for engagement, retention and development may result in unintended consequences including employees attempting to "game" metrics, disengaging and/or leaving the organization.

Deskilling of HR Professionals

HR professionals are at risk of being deskilled as a direct result of automation of routine HR tasks and increased emphasis on data. As the focus continues to increase toward data, there is a fear that HR professionals will become nothing more than curators of algorithmic output as opposed to strategic decision makers (Bélanger & Morselli, 2022). There is also a potential for a two-tiered HR workforce. On one side, there could be a relatively small number of highly skilled data scientists and people analytics professionals. On the other hand, there would be a much larger pool of transactional HR staff with limited authority and responsibility to influence business decisions. To avoid creating a bifurcation of the workforce that creates problems for all involved parties, organizations must take proactive steps to ensure that HR professionals continue to develop their understanding of algorithms and how they can use them without losing sight of their subject matter expertise (Cheng & Hackett, 2021).

Legal and Regulatory Risks

In addition to GDPR, a patchwork of regulatory bodies is developing around the world. For example, New York City's Local Law 144 (effective in 2023) requires bias testing of all automated employment decision tools. Similarly, the EU AI Act would classify AI systems utilized in employment as "high-risk," requiring conformity assessments, transparency, and human oversight. Because the regulatory environment is rapidly evolving, organizations utilizing AI in HR run the risk of significant reputational and financial damage if they utilize AI systems that are discriminatory or non-compliant (Hunkenschroer & Kriebitz, 2023).

Ethical and Legal Implications:

Developing a Framework for Responsible Use of AI in HR

Development of Responsible AI

While still in its infancy stages, existing frameworks for responsible AI in HR are already beginning to emerge. Two notable examples include the European Commission's High Level Expert Group on Artificial Intelligence and academic/organizational ethics literature. These sources suggest five key principles for responsible AI in HR: Fairness (i.e. avoiding unfair bias); Accountability (i.e. clearly identifying which individual(s) are accountable for the results generated by an AI system); Transparency (i.e. providing clear explanation for why an AI system generates a particular outcome); Privacy (i.e. respecting employees' personal information/data); and Human Agency/Oversight (i.e. ensuring that humans are able to evaluate the relevance and appropriateness of an AI-generated recommendation before accepting it as valid) (European Commission, 2019). While the importance of each principle is well established within both academia and industry circles, translating these principles into practical application for organizations remains a difficult task.

Explainable AI (XAI)

Explainability is crucial since all HR decisions require supportable rationale both to justify decisions made to employees and to defend against regulatory scrutiny. Deep-learning models are particularly problematic due to their inherently opaque nature. More recent advancements in explainable AI (XAI) such as LIME and SHAP provide post-hoc explanations of what factors influenced model predictions but these explanations can be misleading or incomplete (Rudin, 2019). Therefore, when considering whether to adopt XAI technology in HR applications that result in significant consequences to employees, some researchers advocate for the adoption of simpler models that produce transparent interpretations (e.g. decision trees, logistic regression) regardless of the reduction in predictive accuracy (Cheng & Hackett, 2021).

Human-in-the-Loop/Augmented Intelligence

There is growing agreement among experts advocating for augmented intelligence instead of complete automation. With this approach, AI provides recommendations/insights/flags; however, ultimately the final decision regarding significant matters related to employees remain with humans. Despite this approach having merit as far as reducing the risks associated with bias/fairness issues inherent in fully automated systems, research conducted by Van Den Broek et al. (2021) indicates that simply implementing human-in-the-loop does not solve all problems. In fact, Van Den Broek et al. (2021) showed that when humans receive confident AI-recommendations they frequently do not critically evaluate them (automation bias); conversely, when humans receive conflicting/noisy/uninterpretable AI-recommendations they often ignore them. Therefore, effective implementation of human-in-the-loop systems requires educating/training HR professionals to not only recognize/interpret AI outputs but also to think critically about them and maintain epistemological vigilance. Therefore, organizations must create new competency standards for HR professionals that incorporate both analytical capabilities with ethical considerations and social-interpersonal judgment capabilities.

Co-Design and Employee Voice

The co-design of people analytics systems and the voice of employees are both important issues that are currently underdeveloped. An example of the lack of engagement of employee representatives in the development of people analytics systems can be seen in management and IT developing these systems alone without input from employee representatives. Employees may view such systems as lacking in privacy, fAIr, etc. Co-designing of people analytics systems that incorporate representative workers, ethicist's and behavioral scientist's will provide for a variety of perspectives and improve the legitimacy of the people analytics system (Giermindl et al. 2022). Additionally, as unionization increases across industries, collective bargAIning related to algorithmic management will likely become an increasingly important area. "Algorithmic Due Process" provides procedural justice through AI-based mediation for decisions made based on the application of algorithms. As such, employees should receive notice regarding when algorithms are applied to make decisions, have access to the reasoning used to generate those decisions and have a reasonable means to dispute and/or correct errors associated with the decisions (Kim & Scott, 2021).

Future Directions and Conclusion

Future Research Areas

While the body of knowledge around AI and people analytics continues to grow at a rapid pace, it does so with many gaps that researchers should consider filling. Specifically, there exists a significant gap in the empirical research linking AI-based technology in HR to tangible business results, not simply operational efficiencies, but employee wellness, diversity, innovation and sustainable value creation. A considerable portion of the existing research is anecdotal in nature or provided by vendors. Longitudinal research is needed to assess how continuous exposure to algorithmic management will influence employee motivation, creative output and mental/physical health. It would be beneficial to investigate the interplay between government regulations and organizational practices concerning AI-based HR technologies as laws specific to AI continue to develop. There remains a relative dearth of research on the perspective of employees on AI-based HR technologies; qualitative and participatory methods could provide insight on various demographic experiences with AI-based HR technologies and resistance to them. Lastly, generative AI (i.e., large language model) has the potential to dramatically alter HR-related functions (i.e., drafting job postings, performance reviews, etc.) and create new ethical considerations surrounding authenticity, bias amplification and job replacement.

Conclusion

AI and people analytics represents a paradigmatic shift in HR decision making. Data and algorithms are becoming integral components of talent management. The potential advantages of AI are significant and already evident in many areas which includes improved efficiency, greater objectivity, individualized development opportunities, and enhanced strategic workforce insights. Nevertheless, this paper has demonstrated that the dangers presented by the increasing reliance on algorithmic HR tools are significant as well. While much attention has been given to the technical limitations of relying on algorithms in managing employees, this paper argues that the danger posed by algorithmic HR tools go far beyond simple technical bugs that will eventually be resolved; rather they are inherent aspects of utilizing algorithmic systems in an employment relationship defined by unequal levels of power and conflicting definitions of what constitutes merit. Ultimately, the primary issue facing companies today is that AI represents a very specific image of human capital (i.e., quantifiable, predictable and optimized) that is difficult to reconcile with the relational, developmental and ethical nature of HRM. If left unchecked, algorithmic management poses the threat of reducing trust among employees, further entrenching inequality among employees and dehumanizing employees by transforming them into passive recipients of obscure computer-based decisions. Rather than adopting a technologically utopian approach to the implementation of AI in HR or rejecting its adoption altogether, companies must work towards creating a human centered, augmented intelligence paradigm. To achieve this end, companies must integrate ethics into each step of the analytics lifecycle; invest time and resources into providing algorithmic literacy training for both HR personnel and employees; implement effective governance mechanisms; and ultimately maintain real human judgment in decisions that greatly affect employees' livelihoods. Scholars within academia have an essential responsibility in producing independent research that will inform practice and policy. Through facilitating dialogue among disciplines and holding organizations accountable, scholars can ensure that the revolution in AI in HR is not limited solely to improvements in efficiency and profit; but rather contributes to social justice, human dignity and human flourishing.

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