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Editorial Introduction

As artificial intelligence becomes more sophisticated, automated decision-making is replacing human decisions about work, management and employment issues. This Briefing Paper draws on research, media sources and legal cases relating to automated work and employment to investigate the implications of this broad transformation to the digital management of work. Three dimensions of work and employment are discussed where digital management is already having a significant impact: recruitment and selection, task allocation and measuring productivity. The types, capacities and impacts of automated technologies are examined.

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Automated management in work and employment

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Introduction

Technology has long been a tool to support management. New automated systems, however, represent a fundamental shift in the scale and capability of complex management practices that once required human decision-making. The deployment of automation and artificial intelligence (AI) in employment settings constitutes the convergence of a broad range of interrelated technologies and methods, including monitoring software, tracking devices, sophisticated algorithms, machine learning, natural language processing, speech recognition, computer vision and Generative AI.

AI in recruitment and selection

AI-enabled tools have fundamentally changed candidate recruitment and selection from a people-driven process to an automated one. Today, AI-enabled recruitment systems offer a cost-effective means to attract a large and diverse group of qualified job seekers, agility in rapidly responding to changes in the labour market, and the ability to free up resources for other human resource (HR) functions (Köchling & Wehner, 2020).

AI tools can be deployed across four phases of recruitment: outreach, screening, assessment and coordination (Black & van Esch, 2020). In ***outreach***, AI tools such as Textio learn presentation methods (e.g., banner ads, email, text) and optimise the wording of job ads to target specific applicant pools. Candidates are then ***screened*** through automatic review of resumes against criteria to compile a shortlist of applicants.

AI is ***assessing*** job candidates via automated video interviewing (AVI), which may score individuals on language and facial expressions (McColl & Michelotti, 2019), screen for qualities like 'grit', and use verbal and non-verbal behaviours to make personality assessments (Hickman et al., 2022).

The ***coordination*** of recruitment activities is also being automated. AI chatbots such as Nuance can engage with candidates in real time, answer questions, ask for missing information, schedule interviews and notify candidates of progress. AI-enabled recruitment can improve the efficiency of recruitment processes for both candidates and employers, while raising new challenges.

Impacts of automated recruitment and selection

The first challenge is ***transparency.*** Most systems operate without specific requirements to disclose how they select, rank and hire candidates. Companies, governments, NGOs, and academics have dedicated substantial efforts to address this ethical problem, generating AI ethics principles and statements (Jobin et al., 2019), yet these principles say little about accountability in
recruitment practice.

Another challenge is ***validity.*** Recruitment validity may be threatened if candidates can game, disrupt or manipulate their responses to an automated system (Tambe et al., 2019) or use generative AI to craft an ideal, but inauthentic job application. Conversely the validity of sentiment analysis or affect recognition during selection interviews is questionable, especially in light of research which confirms that facial movements may convey contextual information beyond the person's emotional state (Barrett et al., 2019).

Bias and discrimination has received increasing attention. A recurrent justification for the use of AI is that it can eliminate individual bias of human recruiters because the systems apply objective and neutral criteria (Bodie et al., 2017). Yet studies have already demonstrated that algorithms can reproduce existing social and labour market inequalities when base training data is derived from a limited, relatively homogenous population (Hunkenschroer & Luetge, 2022; Zajko, 2022).

Consequently, AI-enabled recruitment presents ***inequitable risks and benefits to job candidates.*** Job seekers with limited digital skills or access to technology (e.g., older people, those with a disability or those who live in remote areas) may be particularly negatively impacted by the automation of recruitment (Hunkenschroer & Luetge, 2022).

The allocation of jobs and tasks through AI

Algorithms are used to implement 'just-in-time' work practices, offering workers shifts or contract work according to expected business demand (Ulmer & Savelsbergh, 2020). Automated shift allocation algorithms forecast customer footfall, using traffic history, point of sale data and weather forecasts. Low-wage workers, especially in retail and hospitality, are disproportionately subject to automated scheduling (Van Oort, 2019).

In the gig economy, worker reputation and rating mechanisms are used to measure worker performance and to control or restrict access to work. Beyond the gig economy, such as in restaurants, individual waiters can be rated by patrons or their employers via an app. Some questions ask about factors over which wait staff have no control such as the quality of the food and condition of the restaurant (O'Donovan, 2018).

Impact of automated task and work allocation algorithms

Shift allocation algorithms can benefit workers by giving clearer advance notice of available work and the ability to change shifts. This may avoid shifts being cancelled or cut short with very little notice. Based on customer data, scheduling algorithms can also result in shorter shifts and illogical schedules that are unresponsive to workers' and even managers' needs (Levy & Barocas, 2018).

Automated approaches to tracking and evaluating productivity

Algorithmic management systems, such as shift management apps, can provide workers with convenience and a sense of autonomy and, in tandem, greatly enhance employers' capacities to direct, evaluate and discipline employees, beyond what could be accomplished through other, less invasive forms of control.

Workplace surveillance systems collect data through handheld devices, point-of sale systems, mobile phones, fingerprint scanners, fitness and wellness apps, GPS trackers, smart cameras, microphones, web cams, body sensors, and tools that scan emails and texts. These systems serve multiple purposes including identifying the uneven distribution of work and the most innovative workers, as well as tracking application usage and web history, assessing productivity, detecting deviant behaviour and reporting business intelligence data analytics (Rosenblat et al., 2014). The COVID-19 pandemic ushered in a golden age of digital surveillance. Within weeks of the start of the pandemic in the US, sales of Sneek online surveillance software increased tenfold and the software Prodoscore saw interest from prospective customers rise by 600% (Isaak, 2020).

Data-centric technologies often deployed in the name of ***safety*** come in the form of fitness apps, safety belts, and even mattress sensors to track sleep. With the aim of improving worker wellbeing and reducing incidents, these devices are sometimes offered to workers as part of health and wellness programs.

The employers using biometric systems most prolifically are concentrated in low-wage, hourly work industries such as construction, hospitality, retail, agriculture and logistics (Mateescu & Nguyen, 2019). These contexts are more susceptible to datafication because tasks are more easily measured.

Impacts of surveillance to track and evaluate employee productivity

The impacts of surveillance that tracks and evaluates employee productivity include ***technologically-driven speedups.*** Amazon led the way with a video game called Mission Racer that makes workers compete with each other to fulfill orders. Turning work into a race contrasts with accepted principles of engineering and consequently, the injury rate for their workers is twice other private industries (Gutelius & Theodore, 2019).

There are also growing concerns that surveillance can ***inhibit the ability of workers to engage in collective action*** or attempt to change workplace conditions. For example, retailer Whole Foods uses data about location of nearby unions, union membership, and local poverty and unemployment levels to create a "heat map" that tracks potential unionization at its stores (Peters, 2020).

The use of biometric systems also raises ***privacy*** issues. Information collected is often combined with third party data sources. Monitoring also blurs the line between work and home, and in the case of sleep monitoring apps, invites an employer's surveillance tech literally into bed with a monitored worker.

There may also be ***data limitations*** in biometric systems. The elderly and manual workers often have damaged or abraded fingerprints and people with dark eyes/large pupils have difficulty using iris recognition systems (Franks & Smith, 2021). A person's race can influence how facial recognition software interprets facial expressions (Leslie, 2020).

Transparency is also problematic when surveillance is hidden, multifaceted and continuous. For example, Walmart workers were asked to download the "Me@Walmart" app onto their personal devices to check inventory, clock on, manage shifts and communicate with managers. Managers did not tell workers that app functions require access to cameras and location services and continually runs unless the employee turns it off (Wayt, 2021).

Policy debates about surveillance and unregulated data collection have primarily focused on consumers rather than workers (Okazaki et al., 2020) and the law provides few boundaries. Generally, cameras are prohibited in intimate settings such as bathrooms, and in the US, some states have enacted workplace privacy laws where employees can decline to have a tracking microchip implanted in their bodies (Nguyen, 2021).

However, beyond these narrow limitations, employers can generally condition employment on workers' consent to a variety of monitoring practices (Ajunwa et al., 2017).

Conclusion

The perpetual surveillance and optimisation of worker performance is a growing feature of contemporary work practices. Privacy advocates caution that the tools we create today constitute a surveillance "inertia" that will shape data collection practices well into the future (Hartzog, 2018), and potentially increase the power of technology companies that design the systems that collect and store the data. Scholars, regulator and labour representatives have suggested various forms of protection for workers from the proliferation of automated management strategies (Capel & Brereton, 2023).

In relation to privacy, regulation (which varies across jurisdictions) does not always specify the limits of when and what employee data, including biometric data, can be collected, retained or disclosed (Sprague, 2018). Employers in many jurisdictions can also retain employees' biometric data after they have left the company. This makes employers one of the largest collectors of data, and one with nearly unchecked authority. There is consequently a need for more legal limits on employers' rights to surveil, and expanded privacy rights for workers (Nguyen, 2021).

Transparency also warrants attention, particularly around AI-enabled recruitment, surveillance and monitoring. Algorithms may improve the efficiency of people management practices, but algorithmic decisions are opaque and difficult for workers to contest if they perceive unfair decisions (Nguyen, 2021).

To mitigate the potential negative consequences, there have been calls for the audit of algorithms used in employment, greater transparency in their use, and close scrutiny of their effects to address discrimination, bias and other harms (Capel & Brereton, 2023; Tambe et al., 2019). There is a further need to illuminate the full range of automated recruitment technologies available to different markets, what industries are targeted by vendors, and what functionality and ethical safeguards they promise. These interventions will need to be multi-faceted, addressing the role of developers and vendors as well as employing organisations.

Finally, there is a need for increased advocacy. Provisions in collective agreements for example, can lay down specific limits to managerial prerogatives such as the monitoring of workers at both the company and sector level, and provide criteria to improve the transparency of AI-based decision-making.

Much history in the automation of work has shown that to ensure work conditions do not erode, holding employers accountable for the conditions of work and workplaces, regardless of the system of control that created the conditions, is critical to protecting workers and maintaining basic workplace standards. The voluntary AI Safety Standard under development by industry and the Australian Government provides a first step, though more work is needed to ensure appropriate safeguards on the surveillance powers of employers, the transparency of algorithmic management, and requirements for technology providers to monitor and mitigate against bias or other potential harm.

References

Ajunwa, I., Crawford, K., & Schultz, J. (2017). Limitless worker surveillance. *California Law Review,* Vol. 105 (3) 735-776 https://doi.org/10.15779/Z38BR8MF94

Barrett, L. F., Adolphs, R., Marsella, S., Martinez, A. M., & Pollak, S. D. (2019). Emotional expressions reconsidered: Challenges to inferring emotion from human facial movements. *Psychological Science in the Public Interest,* 20(1), 1-68. https://doi.org/10.1177/1529100619832930

Black, J. S., & van Esch, P. (2020). AI-enabled recruiting: What is it and how should a manager use it? *Business Horizons,* 63(2), 215-226. https://doi.org/10.1016/j.bushor.2019.12.001

Bodie, M. T., Cherry, M.A., McCormick, M. L., & Tang, J. (2017). The law and policy of people analytics. *University of Colorado Law Review,* 88(4), 961-1042 https://ssrn.com/abstract=2769980

Capel, T., & Brereton, M. (2023, April). What is human-centered about human-centered AI? A map of the research landscape. In Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems. (pp. 1-23) https://doi.org/10.1145/3544548.3580959

Franks, C., Smith, R. G. (2021). *Changing perceptions of biometric technologies. (*Research Report No. 20) Australian Institute of Criminology.

Gutelius, B., & Theodore, N. (2019). The future of warehouse work: Technological change in the US logistics industry. *UC Berkeley Labor Center.* https://laborcenter.berkeley.edu/future-of-warehouse-work/

Hartzog, W. (2018). *Privacy's blueprint: The battle to control the design of new technologies.* Harvard University Press.

Hickman, L., Bosch, N., Ng, V., Saef, R., Tay, L., & Woo, E.D. (2022) Automated video interview personality assessments: Reliability, validity, and generalizability investigations. Journal of Applied Psychology, 107 (8). 1323-1351. https://doi.org/10.1037/apl0000695

Hunkenschroer, A. L., & Luetge, C. (2022). Ethics of AI-enabled recruiting and selection: A review and research agenda. *Journal of Business Ethics,* 178(4), 977-1007. https://doi.org/10.1007/s10551-022-05049-6

Isaak, A. (2020) Employee tracking is increasingly widespread, and it could be doing more harm than good. *CNBC, June 17.* https://www.cnbc.com/2020/06/17/employee-surveillance-software-is-seeing-a-spike-as-workers-stay-home.html

Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence,* 1(9), 389-399. https://doi.org/10.1038/s42256-019-0088-2

Köchling, A., & Wehner, M. C. (2020). Discriminated by an algorithm: a systematic review of discrimination and fairness by algorithmic decision-making in the context of HR recruitment and HR development. *Business Research,* 13(3), 795-848. https://doi.org/10.1007/s40685-020-00134-w

Leslie, D. (2020). *Understanding bias in facial recognition technologies: an explainer.* The Alan Turing Institute. https://doi.org/10.5281/zenodo.4050457

Levy, K., & Barocas, S. (2018). Privacy at the margins I refractive surveillance: Monitoring customers to manage workers. *International Journal of Communication, 12,* 1166-1188. https://ijoc.org/index.php/ijoc/article/view/7041/2302

Mateescu, A., & Nguyen, A. (2019). *Explainer: Workplace monitoring* & *surveillance.* https://datasociety.net/library/explainer-workplace-monitoring-surveillance/

McColl, R. and Michelotti, M. (2019) Sorry, could you repeat the question? Exploring video-interview recruitment practice in HRM. *Human Resource Management Journal,* 29 (4), 637-656. https://doi.org/10.1111/1748-8583.12249

Nguyen, A. (2021). The constant boss: Work under digital surveillance. *Data* & *Society* https://datasociety.net/wp-content/uploads/2021/05/The_Constant_Boss.pdf

O'Donovan, C. (2018) An invisible rating system at your favorite chain restaurant is costing your server, 21 June. *BuzzFeed News*

Okazaki, S., Eisend, M., Plangger, K., de Ruyter, K., & Grewal, D. (2020). Understanding the strategic consequences of customer privacy concerns: A meta-analytic review. *Journal of Retailing,* 96(4), 458-473. https://doi.org/10.1016/j.jretai.2020.05.007

Peters, J. (2020). Whole Foods is reportedly using a heat map to track stores at risk of unionization. The Verge. https://www.theverge.com/2020/4/20/21228324/amazon-whole-foods-unionization-heat-map-union

Rosenblat, A., Kneese, T., & Boyd, D. (2014). *Workplace surveillance.* Open Society Foundations' Future of Work Commissioned Research Papers 2014. https://dx.doi.org/10.2139/ssrn.2536605

Sprague, R. (2018). Survey of (mostly outdated and often ineffective) laws affecting work-related monitoring. Chicago-Kent Law Review, 93 (1), 221-253 https://scholarship.kentlaw.iit.edu/cklawreview/vol93/iss1/8

Tambe, P., Capelli, P., & Yakubovich, V. (2019) Artificial intelligence in human resources management: Challenges and a path forward. *California Management Review,* 61(4), 15-42 https://doi.org/10.1177/0008125619867910

Ulmer, M. W., & Savelsbergh, M. {2020). Workforce scheduling in the era of crowdsourced delivery. *Transportation Science,* 54(4), 1113-1133. https://doi.org/10.1287/trsc.2020.0977

Van Oort, M. (2019). The emotional labor of surveillance: Digital control in fast fashion retail. *Critical Sociology,* 45(7-8), 1167-1179. https://doi.org/10.1177/0896920518778087

Wayt; T. (2021). Walmart's free phones for employees raise privacy concerns, experts say. *New York Post, June 8.* https:nypost.com/2021/06/08/walmarts-free-phones-for-employees-raise-privacy-concerns-experts/

Zajko, M. (2022). Artificial intelligence, algorithms, and social inequality: Sociological contributions to contemporary debates. *Sociology Compass, 16(3),* https://doi.org/10.1111/soc4.12962

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