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The New Digital Divide: A Perspective of AI Literacy as Workplace Capital and Organizational Inequality

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ABSTRACT

In the business world, workplace relationships, employee work performance, and business decision-making are all currently being transformed by the broad diffusion of generative Artificial Intelligence (AI). This explosion focuses on productivity effects; however, it is unaccompanied by studies on whether divergent degrees of AI expertise can produce novel labour inequities. This perspective relied on prior work in the fields of AI literacy, the digital divide, human capital, organizational justice, and human-AI teams. This article conceptualizes the AI Literacy Divide. It argues that literacy in AI is becoming a type of workplace capital that mediates whether an individual can translate access to AI to enhance productivity, work quality and career progression. High-AI literacy workers could be relatively privileged recipients of a variety of rewards associated with AI-enabled work, while low-AI literacy workers could be relatively excluded or disadvantaged relative to their work counterparts possessing equivalent levels of non-AI-based work knowledge. We presented a framework on the origins and effects of the AI Literacy Divide and discussed the practical implications for HR management, human capital management, organisational equity, and future research.

Keywords: Artificial Intelligence Literacy; Workplace Capital; Digital Divide

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INTRODUCTION

GenAI is a part of modern knowledge work: helping automate tasks and analyze information (Budhwar et al., 2023; Noy & Zhang, 2023). Yet just giving access does not create an even playing field. Not all employees can properly judge the accuracy and potential bias of GenAI output, combine the generated information with domain expertise, and apply the output responsibly. Thus, the same technology might make one employee perform better, and another dependent or excluded.

We understand elements of the problem but not the complete mechanism creating the workplace inequality. Studies of AI literacy define the skills that are needed to critically interact with AI (Long & Magerko, 2020; Cetindamar et al., 2024; Chiu, 2025), but tend to consider literacy an individual capacity, and do not explain how literacy leads to career success. Digital divide theory has evolved from equal access to unequal skills, usage and outcomes (van Deursen & van Dijk, 2019; Robinson et al., 2020; Lythreatis et al., 2022), but does not account for how organisational dynamics shape differences in skill to different forms of social capital (recognition, rewards, mobility).

Human capital theory, in contrast, can address why skill premiums occur as the value that employees create (Gerhart & Feng, 2021), and existing research on AI at work notes the value that it adds by supplementing human judgment (Raisch & Krakowski, 2021; Noy & Zhang, 2023). But how is that value noticed by managers and facilitated through other resources and HR processes to be continued and built upon? To be precise, current theories cannot fully explain why two employees who have similar vocational knowledge and are exposed to AI would have divergent careers.

This article addresses that gap by theorizing that AI literacy divides the sustained variation in the understanding, critique and constructive application of AI by employees that is enacted into disparate career outcomes through organizational structures.

It does so by conceiving of AI literacy as a form of workplace capital, by representing how value may be realized through AI in the form of a pipeline that flows from decision quality to knowledge sharing to organizational outcomes and impact and reputation, and by explaining how organizational contexts can amplify or minimize such a divide.

LITERATURE REVIEW

AI Literacy as an Emerging Workplace Competency.

The understanding of AI literacy has been described as capabilities and capacity to effectively and critically engage with AI technologies (Long & Magerko, 2020; Cetindamar et al., 2024). Further generalised the concept of AI literacy into workplace contexts and defined it as an employee's capacity to understand, critically analyse, and effectively use AI technologies. There is extensive evidence demonstrating a positive relationship between workplace outcomes and AI literacy. For example, Liu et al. (2025) found that generative AI literacy could positively influence employees' job performance and self-efficacy in creativity. Chiu (2025) elucidated that AI literacy is multidimensional in terms of knowledge of AI technologies, ability to evaluate, critical and responsible

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application, and awareness of AI-related ethical implications. AI-literate employees will be better able to use AI technologies and thus achieve better work performance.

Digital Divide Theory

Work dealing with the digital divide offers valuable insight into the inequalities involved with AI usage. The concept first described gaps in technology access; however, it also extends to digital skills, uses and outcomes (Van Deursen & Van Dijk, 2019). Robinson et al. (2020) proposed that contemporary digital divides are multifaceted and informed by socio-economic as well as technical factors. According to Lythreatis et al. (2022), digital inequality increasingly refers to people's ability to achieve significant benefits from technologies. Now that access is so ubiquitous, AI literacy might account for a larger proportion of individual differences in outcomes than does access.

Human Capital and Workplace Value Creation

The concept of human capital theory has already been set with the premise that employee skills, abilities, and knowledge yield rewards for increasing levels of productivity and performance. Gerhart and Feng (2021) continue to agree that human capital is critical to attaining a competitive advantage. The study opined that there are various ways in which human capital is utilised and rewarded, and AI can have an effect on these different ways. Call et al. (2026) have concluded that AI has the ability to amplify disparities in individual output, with increased returns for the capabilities in human capital. Another facet of human capital for AI-driven environments may be AI literacy.

Human-AI Collaboration

In terms of human-AI collaboration, it was stressed in the literature that AI works better when complementing rather than replacing human capabilities (Raisch and Krakowski, 2021). The conclusion suggested that there is value in human expertise and AI working in a beneficial partnership (Budhwar et al., 2023), while Noy and Zhang (2023) found empirically that employing generative AI is a significant driver of productivity increases when accompanied by appropriate human capacity for leveraging. The key to deriving human-AI collaborative benefits is human-AI literacy.

The AI Literacy Divide Framework

We propose that the concept of AI literacy is workplace capital that links access to AI in the workplace to work outcomes.

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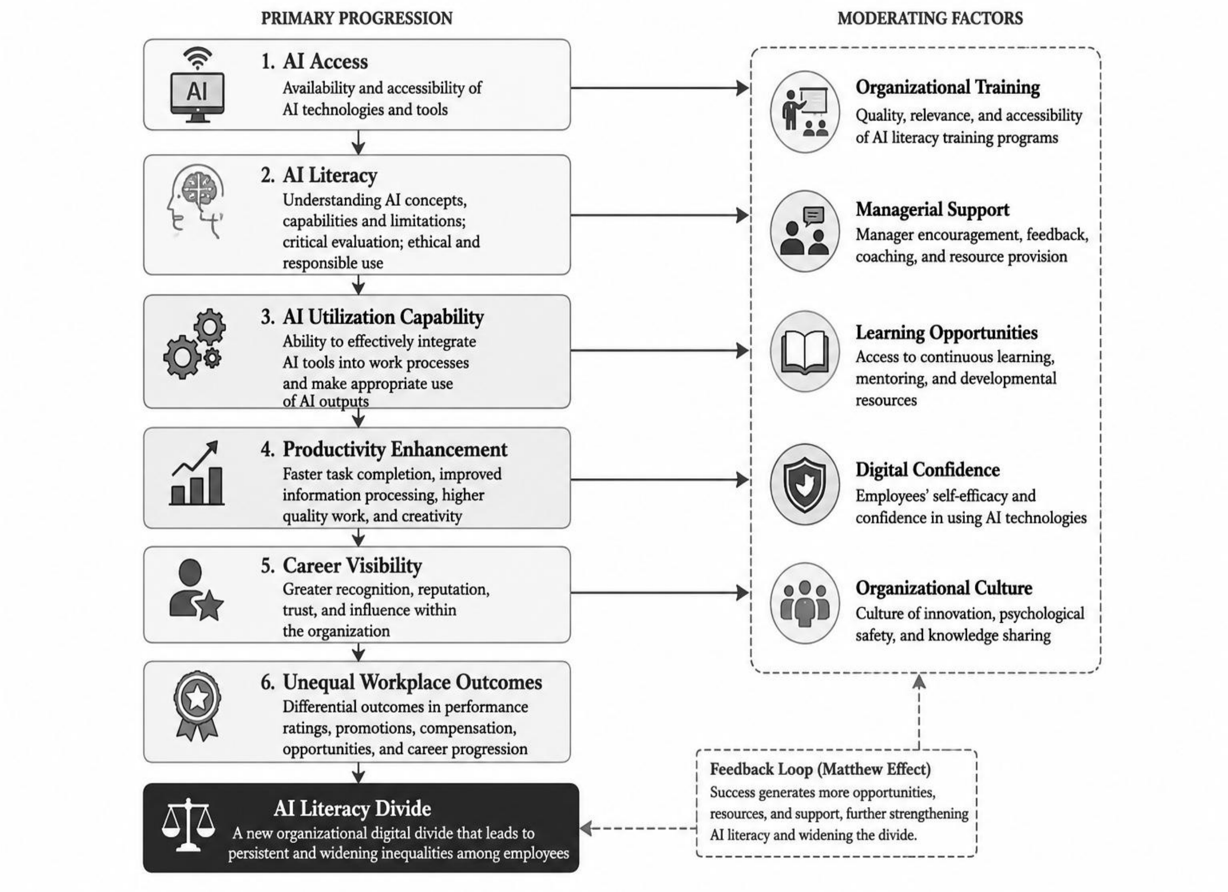

Figure 1. Conceptual Framework of the AI Literacy Divide in AI-Enabled Workplaces
Source: Authors

The framework offers the key process flow below.

1. AI Access: Availability and accessibility of AI technology and tools in the workplace. The provision of access is not enough to bring benefits to the workplace.
2. AI Literacy: The understanding of AI concepts, abilities and limits, and its critical evaluation, and ethical and responsible application.
3. AI Utilisation Capability: The ability to skillfully apply AI tools to work processes and wisely exploit the results from AI technology.
4. Productivity Enhancement: The speed of work, processing of information, quality of results, and increased innovation and creativity.
5. Career Visibility: Image, prestige, trustworthiness and power in the organization.
6. Unequal workplace outcomes: Differences in work appraisal, advancement, pay, opportunities, and careers**.**

There are several moderating variables included in the proposed framework. Each of these factors-Organizational Training (quality, relevancy, and accessibility of AI literacy training), Managerial Support (promotion, coaching, feedback, and resource support), Learning Opportunities (access to ongoing learning and mentoring), Digital Confidence (user's self-efficacy in utilizing AI technologies) and Organizational Culture (innovation, knowledge sharing, and psychological safety) determines whether the inequality gaps will widen or be narrowed.

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Most importantly, the model incorporates a feedback process (Matthew Effect) that, as outcomes are positive, access to opportunities, resources, and support becomes higher, strengthening AI literacy over time, leading to greater inequalities in the organisation. Those organisations that effectively address the training and support for AI literacy among their workforce may actually narrow AI-based disparities, while those that do not equip their workforce with AI literacy knowledge and skills may inadvertently exacerbate the gap by fostering a new digital divide.

RESEARCH RESULTS

Employee Profiles within the AI Literacy Divide

Three major types of employees can be extrapolated from the framework:

- AI-enhanced employees: These employees have strong domain expertise and high AI literacy and will constitute the most competitive labour force. They are able to use human knowledge and AI as complements, and are the most likely to reap advantages from the AI-enabled work system and positive feedback loops initially (success can attract more resources and new opportunities).
- AI-dependent employees: These employees have low critical evaluation ability and tend to use AI frequently. While they may experience higher short-term productivity, they are overly reliant on AI output and likely to fall behind without timely intervention.
- AI-excluded employees: These employees have low AI literacy and/or insufficient opportunity to upgrade their AI skills. These employees have high domain expertise but pose the greatest risk of prolonged disadvantage because of their low competitiveness

DISCUSSION

AI Literacy Divide also provides more literature on digital inequalities and demonstrates how AI literacy could be the next key determinant in the workplace. Unlike other digital divides based on access, an AI-empowered workplace may increase inequality due to differences in workers' effective usage of intelligent technology.

Building upon human capital theory, the model presents the usefulness of AI literacy as an important skill in the workplace. The feedback mechanism reveals the development of widening differences based on small initial advantages.

Concerning the issue of organisational justice, AI literacy is seen to affect workers' perception of the fairness of algorithmic decisions. For instance, a lack of it will lead to workers' perceptions of the non-transparency of AI-powered decision-making, and ultimately, trust in it may be eroded.

Finally, the framework emphasises complementary capabilities in human-AI interaction with organisational culture and management support as enabling factors.

Implications for Human Resource Management

The framework identifies where routine HR decisions may amplify the divide.

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Job analysis and selection. A job-specific understanding of AI literacy will be necessary. By developing structured work samples for evaluation, using a mix of approaches to evaluate verification capabilities, contextual decision-making, and effective usage given background understanding in a specific domain. Access will be an inadequate substitute for aptitude.

Learning & Development. Upon initial diagnostics, differential learning could be deployed to address knowledge gaps around prompting, verification, bias, privacy and integration into work processes. Outcomes across groups should be compared to prevent a bias that only confident employees might choose to undertake optional training.

Performance Review. Beyond throughput, annual reviews should also document quality of decision-making, verification undertaken, information sharing, creativity and responsibility to prevent a focus on AI-powered speed rather than human experience, problem-solving capacity, and ability to prevent future problems.

Recognition, Rewards and Talent Management. In justifying and documenting an AI-enabled achievement worth recognition, managers should articulate new ideas, process improvements or error detection, for instance. HR can track success rate, training/coaching, and pay rises or promotions for AI adopters to flag potential bias.

Workforce Planning. Literacy metrics should be overlaid with skill sets to plan for likely redeployments, rather than label people as redundant from day one. Reskilling and redeployment rates demonstrate an organization's commitment to growing internal talent, rather than creating a two-tier talent structure.

Employee relations and Organisational Justice. Clear guidelines, opportunities for open learning and debate and routes for escalation should be implemented to ensure maximum perception of fairness. HR could evaluate who gets recognition, project allocation and opportunities across diverse employee groups to flag up unfair practice.

CONCLUSIONS

This research note conceptualised the concept of the AI literacy divide. We assumed that AI literacy is a work capital in an AI-enabling organisation, and five moderating factors (training in an organisation, managerial support, learning, digital literacy, culture of an organisation) will shape the bridging or widening of the AI literacy divide. What is more, a feedback effect (Matthew Effect) was designed to explain how an initially small benefit to the AI-enabling group can transform into an everlasting benefit for the small group, and a drawback for the majority group. We stated that organisations must treat AI-literacy not only as a strategy, but also as a fairness issue; otherwise, employees in an AI-enabling organisation would keep receiving benefits, and those in an AI-disabling one would become further disabled without interventions to close the gap. More research needs to be conducted with different types of organisations and different employees in multiple sectors.

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