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Abstract

Purpose: This study aims to examine whether AI literacy promotes workplace equality by exploiting psychological capital and competitive advantage.

Method: The study surveyed entrepreneurs in Indonesia by adopting a mixed data-collection approach that combined online questionnaires and in-person visits. A snowball sampling strategy yielded 467 valid responses.

Findings: AI literacy does not directly create workplace equality, but indirectly through building psychological capital then translates into competitive advantage.

Policy implications: A social policy should integrate AI literacy and psychological capital development into national workforce, education, and entrepreneurship programs so that AI adoption strengthens inclusion, resilience, and equality rather than reinforcing existing social divides.

Value: This article considers AI as a social amplifier by showing that inclusive outcomes emerge not from AI itself, but from how AI reshapes human confidence, agency, and strategic capability.

Introduction

Main literature widely supports the view that artificial intelligence (AI) promotes firm performance and innovation, thereby contributing to competitive advantage. Kemp (2023) highlights the AI-driven competitive advantage to explain how firms develop cost-efficient capabilities aligned with strategic opportunities to generate sustainable value. However, the capacity to serve as a durable source of competitive advantage diminishes when AI technologies become increasingly inexpensive, ubiquitous, and inclusive. This trend compels firms to reconsider how AI reshapes competitive dynamics rather than assuming inherent strategic benefits (Wingate et al., 2025).

Teece (2023) further argues that AI transforms the competitive advantage by strengthening firms' dynamic capabilities to sense opportunities, seize innovations, and reconfigure resources within complex digital ecosystems. These advantages accrued disproportionately to large platform-based companies, such as Big Tech and organizations, which adopt AI more rapidly and extensively. As a result, there is an uneven distribution of productivity and growth effects of AI across firms and value chains, raising concerns that accelerated AI adoption may exacerbate existing market inequalities (Aghion et al., 2024).

Beyond firm-level outcomes, AI also raises critical issues of equality at the organization and policy levels. UNESCO (2021) indicates that AI literacy provides a pathway to greater equality by enabling individuals to access new opportunities in education, employment, and digital services (Wang, Rau, & Yuan, 2022). However, an exclusive focus on individual skill acquisition risks obscuring institutional responsibility from discriminatory design practices and broader issues of power, representation, and democratic accountability in AI governance (Benjamin, 2019; Rönnblom et al., 2023; Park et al., 2025).

Despite growing recognition of AI literacy as a critical individual capability, existing studies conceptualize it as technical and cognitive competence for engaging with complex and uncertain AI systems, including awareness of ethical and compliance risks (Benlian & Pinski, 2025). However, existing research largely overlooks how AI literacy operates within organizational and institutional contexts. Biagini (2025) calls for navigating the AI-driven world with ethical reasoning, equitable access, and responsive practices.

Against this backdrop, this article examines how AI literacy relates to workplace equality by analyzing the mediating roles of psychological capital and competitive advantage. This study conceptualizes AI literacy as a socially embedded organizational capability that shapes how

AI systems are interpreted, governed, and enacted in everyday work practices. The next section develops the theoretical foundation by reviewing the literature on AI literacy, dynamic capabilities, psychological capital, and inequality regimes, and by formulating a set of testable hypotheses. This framework is then empirically examined using survey data, allowing the study to clarify how human-centered capabilities condition the performance and equity outcomes of AI adoption.

Literature Review

AI Literacy and Competitive Advantage

The resource-based and dynamic capabilities theory shows that value creation arises from integrating knowledge, interpreting AI outputs, and reconfiguring resources under uncertainty (Teece, 2023). AI allows firms to build a competitive advantage not simply by automating tasks but by integrating knowledge and capabilities across domains in novel ways (Krakowski et al., 2022). AI literacy strengthens competitive advantage by enabling firms to convert AI from a generic technology into a strategic resource.

As a strategic resource, AI enhances organizational creativity and productivity, allowing firms to generate sustained value from AI-driven intangible assets and support innovation-led growth (Mikalef et al., 2021; Brynjolfsson et al., 2021). However, firms can no longer rely solely on AI adoption to differentiate themselves, as AI technologies become increasingly standardized and widely accessible (Wingate et al., 2025). Instead, competitive advantage increasingly depends on firms' capabilities to seize opportunities, generate innovations, and reconfigure resources in AI-enabled environments.

AI literacy plays a pivotal role in strengthening the firm's dynamic capabilities by enabling managers and employees to recognize where AI creates value (awareness). As firms effectively deploy AI systems, critically evaluate AI outputs , and anticipate ethical implications (ethics), AI literacy supports opportunity sensing and informed decision-making (Wang, Rau, & Yuan, 2022). These competencies enable firms to move beyond experimental adoption toward purposeful AI deployment, thereby enhancing their capacity to seize innovation opportunities amid business uncertainty (Gama and Magistretti, 2025).

Empirical evidence highlights the importance of such capability-based differentiation. Babina et al. (2024) show that AI investment drives firm performance primarily through product innovation rather than cost reduction, with gains concentrated among firms that effectively integrate AI into their strategic and organizational processes. At the same time, AI's predictive advantages remain constrained under conditions of Knightian uncertainty, where novelty and competitive recursion limit full computability (Townsend et al., 2024). Under these conditions, AI literacy becomes critical for managerial decision-making, enabling firms to interpret AI outputs, recognize their limitations, and reconfigure resources accordingly.

Research on human–AI partnership further reinforces that organizations achieve superior problem-solving outcomes when humans and AI interact through structured hybrid processes—autonomous, sequential, and interactive search—particularly in exploratory tasks (Raisch & Fomina, 2024). Such hybrid processes require high levels of AI literacy to coordinate human judgment and algorithmic capabilities effectively. Together, these insights suggest that AI literacy serves as a microfoundation for dynamic capabilities, enabling firms to translate ubiquitous AI technologies into sustained competitive advantage (Gao et al., 2025).

H1: AI literacy positively determines competitive advantage.

AI literacy and workplace equality

AI literacy promotes workplace equality by enabling responsible governance of AI systems. Inequality regimes theory and responsible AI scholarship show that fairness improves when organizations actively manage access, transparency, and accountability in AI use (Acker, 2006; Healy et al., 2019). Research on AI governance highlights the role of informed human oversight and participatory design in fostering inclusive outcomes (Danaher, 2024; OECD, 2022). Through these mechanisms, AI literacy empowers organizational members to identify, question, and correct biased practices, supporting more equitable workplaces.

AI supports equality only when organizations adopt a balanced approach to its design, deployment, and governance (Wingate et al., 2025). Structural factors such as access, control, surveillance, and digital divides shape unequal AI outcomes, often reproducing existing power asymmetries. Bircan and Özbilgin (2025) demonstrate how these dynamics generate inequality while arguing that co-ownership of AI systems and legal recognition of AI agents strengthen accountability and promote fairness. In contrast, when organizations allow AI systems to rigidly dictate decisions, execution, or creative outputs, they restrict human judgment, improvisation, and creativity, leading to suppression, alienation, or excessive dependence on technology (Ma & Su, 2025).

AI changes how organizations approach equality by forcing them to make choices about access, design, and deployment. These decisions can either support equal opportunity or change the technology's moral direction (Danaher, 2024). Gregory et al. (2021) show that AI systems learn by interacting with users, creating feedback loops. More use improves performance and draws in more people, supporting inclusion. Milkau (2019) shows that AI data platforms create value by turning data into insights and improving services. These platforms support user-organization interactions, but the distribution of benefits depends on governance decisions.

AI affects workers and consumers through automation and decision support. This impact relates to rights, equality, job quality, and education. The OECD (2022) notes that these effects depend on responsible design and governance rather than the technology itself. Research on inequality situates these effects within established theoretical frameworks. Healy et al. (2019) and Nkomo & Rodríguez (2019) demonstrate that Acker's inequality-regimes model has broad applicability. It is used across corporate, public, and agricultural areas and is extended to intersectional and global contexts. This model helps examine how AI can reinforce or challenge workplace inequalities.

H2: AI literacy positively determines workplace equality.

AI literacy and psychological capital

Psychological capital studies primarily draw on resource-based frameworks such as conservation of resources, psychological resource theory, and the job demands–resources model, which conceptualize capital as a set of interrelated psychological resources (Reichard et al., 2025). Hence, AI shapes workplace equality through organizational decisions about how firms design, access, interpret, and govern systems, rather than through technological inevitability (Danaher, 2024; Wingate et al., 2025). Deploying AI without sufficient human oversight, unequal access, surveillance asymmetries, and rigid automation amplifies the existing workplace inequalities (Bircan & Özbilgin, 2025; Ma & Su, 2025).

AI-literate staff engage in governance that promotes transparency, accountability, and access. They examine data sources, monitor feedback, and adjust system use to address unequal outcomes (Gregory et al., 2021; Milkau, 2019). AI literacy allows members to assess algorithmic fairness and challenge automated choices that may be unethical or non-inclusive (Wang, Rau, & Yuan, 2022). These practices fit with the inequality regimes theory. This theory holds that everyday routines and rules can drive systemic inclusion or exclusion (Healy et al., 2019; Nkomo & Rodríguez, 2019).

H3: AI literacy positively determines psychological capital, which in turn promotes workplace equality.

Psychological capital and competitive advantage

Psychological capital (PsyCap) refers to an individual's positive psychological state of development, entailing four interrelated resources: self-efficacy, hope, optimism, and resilience, which yield substantial motivational and performance benefits through transformational leadership (Luthans et al., 2007). PsyCap also demonstrates collective psychological resources that foster entrepreneurial activity and support organizational success (Tjimuku et al., 2025).

PsyCap helps firms gain an edge by building employees' ability to perform during uncertainty, pressure, and opportunity. People with high PsyCap keep working through challenges, find new solutions, and stay motivated. These behaviors improve productivity and performance (Grözinger et al., 2022). PsyCap also supports adaptable, resilient practices. For example, Akroyd, Matsugi, and Shima (2025) show that management systems remain stable within the existing culture but adapt to new demands. This example shows how intangible resources support both stability and innovation.

By building positive psychological resources, organizations use PsyCap to drive performance. PsyCap improves decision-making, problem-solving, and teamwork, letting firms respond to change better than rivals. Leadership style, culture, and setting matter too.

Loghman et al. (2023) show that PsyCap's effects on performance, engagement, and burnout are shaped by these factors. This confirms its importance for long-term advantage.

H4: Psychological capital positively affects competitive advantage

Psychological capital and workplace equality

PsyCap advances workplace equality by enabling employees to engage constructively with organizational challenges. Previous studies combined inequality regimes theory and conservation of resources theory to show that employees with higher psychological capital cope more effectively with stress, manage perceptions of unfairness, and participate more fully in organizational processes (Tafvelin & Keisu, 2024; Lee et al., 2022). Further evidence indicates that psychological capital empowers underrepresented groups to leverage opportunities when supportive leadership and policies are in place (Widiati et al., 2025).

Psychological capital functions as a non-stigmatizing, inclusive resource that directly promotes workplace equality by enhancing employees' resilience, optimism, self-efficacy, and hope. Employees with higher PsyCap cope more effectively with stress, manage perceived unfair treatment, and engage constructively with colleagues, thereby reducing the adverse effects of inequality and fostering equitable participation in organizational processes (Luthans & Broad, 2025; Lee et al., 2022). For instance, Widiati et al. (2025) show that female managers' digital innovation behavior is driven by PsyCap and high-quality leader–member exchange, demonstrating how PsyCap empowers underrepresented groups to leverage opportunities in supportive organizational contexts.

Scholars caution that individual literacy alone cannot overcome these structural disparities, as privileged groups control the majority of access to AI education and skill-building (Eubanks, 2018). Fair and inclusive AI use requires socio-relational responsibilities, prompting future interventions to move beyond anti-discrimination techniques toward technical and policy tools that embed deeper ethical and equity values (Giovanola & Tiribelli, 2023). Moreover, PsyCap strengthens the impact of workplace equality policies by enabling employees to transform structural and procedural interventions into positive experiences and outcomes. Research shows that gender moderates the relationship between PsyCap and well-being, indicating that organizations need both PsyCap development and gender-sensitive policies to achieve equal outcomes (Momin & Rolla, 2024).

H5: Psychological capital positively determines workplace equality.

Competitive advantage and workplace equality

Dynamic capabilities theory suggests that firms pursuing long-term performance invest in fair compensation, employee participation, and inclusive governance (Teece, 2023). Moreover, there has been a dispute over whether equality drives competitive advantage or whether competitive advantage drives equality. When organizations promote equality, they expand access to broader talent pools, strengthen employee commitment, and stimulate creativity and innovation. These equality-driven outcomes become valuable, rare, and hard-to-imitate resources, enabling firms to generate sustainable competitive advantage (Urbancová et al., 2020). Herlitah (2025) confirms that equality plays a pivotal role in unlocking underutilized leadership talent, broadens strategic perspectives, and strengthens dynamic capabilities.

Teece (2023) suggests that competitive advantage reinforces equality when it focuses on innovation, dynamic capabilities, and ecosystem competition rather than mere cost efficiency. By shifting competition policy away from static models that favor incumbents with scale advantages toward frameworks that recognize innovation-driven competition, organizations reduce entrenched market power, limit excessive economic rents, and promote broader welfare gains—thereby creating fairer competitive conditions and supporting more inclusive economic outcomes. Competitive advantage strategies, therefore, do not merely coexist with inequality; they actively shape and structure it, and firms succeed only when perceived inequalities align with employees' fairness expectations (Bao et al., 2025).

H6. Workplace equality supports competitive advantage

Research Method

Measurement

This study employs four core constructs: AI literacy, workplace equality, psychological capital, and competitive advantage and measures them using reflective, perception-based items adapted from established literature. To measure workplace equality, the study adapts items from Tafvelin and Keisu (2024), who define equality as employees' perceived access to influence, resources, and opportunities within the workplace. Consistent with this conceptualization, the items capture employees' perceptions of their influence over work goals and decision-making, access to career development opportunities, job security, compensation and benefits, and the extent of respectful treatment at work.

The study operationalizes AI literacy using the refined measurement framework proposed by Wang et al. (2022). The items assess employees' ability to identify AI technologies embedded in applications, use AI tools effectively to support daily work, improve work efficiency, select appropriate AI-driven solutions, choose suitable AI applications for specific tasks, and adhere to ethical principles in AI use. These indicators reflect both the functional and ethical dimensions of AI literacy emphasized in recent research.

To measure psychological capital, the study adapts items from Luthans et al. (2007), Santos et al. (2018), and Reichard et al. (2025), who conceptualize psychological capital as a positive psychological state comprising self-efficacy, hope, resilience, and optimism. Following this framework, the items assess employees' confidence in presenting their work and mastering new procedures, their ability to generate solutions and pursue work goals, their capacity to recover from setbacks and grow through challenges, and their optimistic expectations regarding future work outcomes.

Finally, the study measures competitive advantage using subjective comparative assessments adapted from prior strategy research (Schilke, 2014; Shafiee, 2021; Pratono, 2022). Consistent with strategic management theory, the study conceptualizes competitive advantage as a firm's relative superiority over competitors rather than absolute performance. This perceptual approach has received broad empirical support and fits survey-based research contexts where objective financial data often remain unavailable or lack comparability across firms.

Data collection

The study targets entrepreneurs in Surabaya City, where the Surabaya Statistics Bureau reports a total population of approximately 150,000 entrepreneurs. To obtain a relevant sample, we applied a combination of snowball sampling and mixed survey methods, considering that most SMEs operate in the informal sector and may be difficult to reach through conventional sampling frames. We distributed online questionnaires to reach a broad audience and conducted in-person visits with trained surveyors to improve response rates and data accuracy. The survey was conducted between October and December 2025, yielding 467 valid responses from SMEs across Surabaya.

Among respondents, 45% were owner-managers, 15% were managers, and the remaining participants were senior staff. Regarding firm size, 45% reported having 1–4 employees, 32% reported having 5–19 employees, and the remaining 23% reported having 20–50 employees. By business sector, 35% of respondents worked in trading, 16% in manufacturing, 42% in services, and 8% in agriculture. This diverse distribution of roles, firm sizes, and sectors ensures that the sample provides a representative snapshot of SMEs in Surabaya City.

Results

Measurement models

The measurement model demonstrates satisfactory reliability and validity across all constructs. We measured AI literacy using seven indicators, with outer loadings ranging from 0.717 to 0.802, indicating adequate indicator reliability. The construct shows strong internal consistency, as evidenced by a Cronbach's alpha of 0.868 and a composite reliability of 0.901. The average variance extracted (AVE) exceeds the recommended threshold at 0.603, confirming convergent validity. Variance inflation factor (VIF) values range from 1.526 to 2.212, indicating no multicollinearity among the indicators (Table I).

Competitive advantage exhibits powerful psychometric properties. All eight indicators load highly on the construct, with outer loadings ranging from 0.788 to 0.841. The construct achieves excellent internal consistency, with a Cronbach's alpha of 0.933 and composite reliability of 0.945. The AVE of 0.681 confirms that the construct accounts for a substantial proportion of variance relative to measurement error. VIF values remain below the conservative threshold of 3.0, indicating no problematic collinearity (Table I).

We measured psychological capital using twelve indicators representing self-efficacy, hope, resilience, and optimism at work. Outer loadings range from 0.717 to 0.835, exceeding minimum acceptable levels. The construct achieves very high reliability, with a Cronbach's alpha of 0.945 and a composite reliability of 0.952. An AVE of 0.625 confirms adequate convergent validity. Although several indicators show relatively higher VIF values, all remain below critical thresholds, indicating that multicollinearity does not threaten the measurement model (Table I).

Finally, we operationalized equality using seven indicators capturing perceived influence, decision-making role, career opportunities, job security, compensation, benefits, and respect at work. Outer loadings range from 0.712 to 0.812, demonstrating satisfactory indicator reliability. The construct achieves good internal consistency, with a Cronbach's alpha of 0.892 and composite reliability of 0.915. The AVE value of 0.607 exceeds the recommended minimum, supporting convergent validity. VIF values between 1.668 and 2.295 indicate that collinearity does not pose a concern (Table I).

Inner models

Table II shows the effect size analysis using f^2 values highlights the central role of psychological capital as a mediator between AI literacy and organizational outcomes. AI literacy exerts a moderate to large effect on psychological capital ($f^2 = 0.561$), showing that improving employees' AI literacy substantially strengthens their psychological resources. In contrast, AI literacy has only a small effect on competitive advantage ($f^2 = 0.043$) and a negligible effect on workplace equality ($f^2 = 0.001$), suggesting that AI literacy alone does not directly translate into these outcomes. Psychological capital, however, demonstrates a moderate effect on competitive advantage ($f^2 = 0.349$) and a small effect on workplace equality ($f^2 = 0.076$), highlighting its key role in channeling the influence of AI literacy into organizational performance and equitable workplace practices.

Table III confirms discriminant validity using the heterotrait–monotrait ratio (HTMT). All HTMT values remain below the conservative threshold of 0.85, establishing that the constructs are conceptually distinct. Specifically, AI literacy shows empirical separation from competitive advantage (0.554), psychological capital (0.651), and workplace equality (0.503). Competitive advantage maintains adequate discriminant validity relative to psychological capital (0.666) and workplace equality (0.770), while the HTMT value between psychological capital and workplace equality (0.661) also stays within acceptable limits .

Table IV evaluated model fit using multiple global fit indices. The standardized root mean square residual (SRMR) of 0.055 confirms a good fit between the proposed model and the observed data. The normed fit index (NFI) of 0.833 indicates acceptable model fit for a complex PLS-SEM model. Additional discrepancy measures, including d_G (0.733) and d_ULS (1.705), show that the empirical correlation matrix aligns closely with the model-implied correlations. Overall, these results confirm that psychological capital mediates the effect of AI literacy on competitive advantage and workplace equality, and that the structural model exhibits strong explanatory power, discriminant validity, and overall fit (Table IV).

Hypotheses test

Table V shows that AI literacy is a foundational capability with statistically significant effects across the model. AI literacy directly determines competitive advantage ($\beta = 0.133$, $p = 0.006$), cultural capital ($\beta = 0.600$, $p < 0.001$), and workplace equality ($\beta = 0.133$, $p = 0.019$). The strong path to cultural capital suggests that AI literacy first reshapes values, norms, and shared competencies before translating into broader organizational outcomes. In other words, understanding AI changes how people think and act long before it changes performance metrics.

The second layer of the model indicates how cultural capital functions as a key transmission mechanism. Cultural capital significantly enhances competitive advantage ($\beta = 0.246$, $p < 0.001$) and has a strong effect on workplace equality ($\beta = 0.531$, $p < 0.001$). This indicates that inclusive values, shared learning, and openness to change are critical for converting technological knowledge into fairer workplace practices. Equality here is not an abstract ideal; it is socially constructed through a culture shaped by AI literacy.

Finally, workplace equality itself emerges as a powerful driver of competitive advantage ($\beta = 0.494$, $p < 0.001$), with one of the strongest effects in the model. This confirms a virtuous cycle: AI literacy builds cultural capital, cultural capital promotes equality, and equality substantially boosts competitiveness. The results imply that competitive advantage is not achieved despite equality, but partly because of it—organizations that translate AI knowledge into inclusive structures gain stronger, more sustainable performance.

Discussion

Theoretical contributions

While previous studies establish that firms generate value from AI by embedding it into organizational knowledge, decision-making, and resource reconfiguration (Krakowski et al., 2022; Teece, 2023), this article extends the discussion by explicitly modeling AI literacy as a microfoundation of dynamic capabilities that operates through individual-level psychological mechanisms. By empirically linking AI literacy to competitive advantage, this study reinforces existing arguments that employees' ability to interpret AI outputs, recognize their limits, and apply AI insights under uncertainty enables innovation-led growth and sustained performance (Mikalef et al., 2021; Brynjolfsson et al., 2021; Babina et al., 2024).

This artice further clarifies the pathways through which AI literacy shapes workplace equality and psychological capital. Prior research emphasizes that AI influences equality through governance, transparency, access, and human oversight rather than technological determinism (Acker, 2006; Healy et al., 2019; Danaher, 2024). Building on this foundation, the study advances theory by positioning workplace equality not as an automatic outcome of AI literacy but as a socially mediated result that depends on intervening human capabilities. Hence, this study highlights psychological capital as a critical explanatory mechanism through which AI literacy enhances employees' confidence, agency, and critical engagement with AI-mediated work processes (Wang, Rau, & Yuan, 2022), enabling voice, bias recognition, and inclusive participation (Gregory et al., 2021; Milkau, 2019).

Finally, the study extends existing theoretical discussion by reconceptualizing psychological capital and workplace equality as strategic resources that jointly reinforce competitive advantage. While prior studies show that self-efficacy, optimism, resilience, and hope drive collaboration and innovation (Luthans et al., 2007; Grözinger et al., 2022; Tafvelin & Keisu, 2024), this study integrates these insights into a single causal structure linking human resources to firm-level outcomes. By theorizing competitive advantage as a driver of workplace equality rather than merely its consequence, the study aligns with research emphasizing innovation-driven performance and inclusive governance (Urbancová et al., 2020; Bao et al., 2025; Teece, 2023). Overall, this article advances the literature by framing AI-enabled competitive advantage as a human-centered dynamic capability.

Policy implications

This article suggests that AI regulation is insufficient to promote inclusive and equitable workplaces. Public policy should integrate AI literacy and psychological capital development into national workforce, education, and entrepreneurship programs, ensuring that AI adoption enhances inclusion, resilience, and equality. Such policies should frame AI literacy as a civic and social capability that enables individuals to critically interpret AI outputs, recognize bias, and exercise agency in technologically mediated work environments.

The results further encourage social policy interventions to extend beyond technical skills training. Given the central role of psychological capital in translating AI literacy into both performance and equality outcomes, social policy should support organizational environments that foster self-efficacy, optimism, resilience, and hope. Public investment in leadership development, lifelong learning systems, and institutional support for experimentation and adaptation is critical to address greater resource constraints in managing information technology turbulence.

Importantly, this study's focus on the weak direct relationship between AI literacy and workplace equality highlights the risk of assuming that access to technology automatically produces fair outcomes. It is essential to social policy to promote clear governance frameworks for organizational AI use, e.g. bias monitoring, transparency requirements, and participatory decision-making mechanisms. These measures help ensure that AI-enabled efficiency gains do not come at the expense of fairness and inclusion, especially for vulnerable or marginalized groups in the workforce.

Finally, the positive relationship between competitive advantage and workplace equality has an important policy implication. Inclusion and performance are not competing objectives; they are mutually reinforcing outcomes. Social policy should encourage organizations to treat workplace equality as a strategic result of AI-enabled growth, not just as a compliance obligation. By embedding inclusive principles into AI-related standards, incentives, and support programs, policymakers can foster sustainable competitiveness. This also strengthens trust, participation, and social cohesion in the evolving world of work.

Research limitation and future studies

This study presents valuable findings while acknowledging several factors that may influence interpretation. The study examined a relatively small sample drawn from a specific population, which may reduce the generalizability of the results to other groups or settings. The research primarily relied on self-reported data, which participants may have influenced through inaccurate recall or social desirability. The study covered a short period, limiting the ability to capture long-term trends or effects. Furthermore, the analysis focused on selected variables, leaving other potentially influential factors unexamined. Future research should expand on these findings by including larger and more diverse samples, employing longitudinal designs to track changes over time, and integrating additional variables to achieve a more comprehensive understanding. Future research also needs to adopt mixed-method approaches and conduct cross-cultural or cross-context studies to generate deeper insights and strengthen the applicability of the results.

Conclusion

This article shows that organizations achieve competitive advantage from AI when managers approach AI literacy as a strategic, human-centered capability and simultaneously invest in employees' psychological capital. Technical proficiency alone does not ensure equitable outcomes; managers must reinforce AI adoption with supportive leadership, transparent governance, and inclusive organizational practices so that performance gains translate into fairness and trust. By embedding equality as a strategic outcome of AI-enabled growth rather than a compliance obligation, organizations should align innovation, competitiveness, and workplace inclusion in a mutually reinforcing way.

Ethical statement

This study involved a minimal-risk, non-clinical survey of adult participants in their professional roles. Data were collected anonymously, no sensitive or personally identifiable information was obtained, and participation was fully voluntary with informed consent. The research involved no intervention, deception, or vulnerable populations and adhered to established ethical standards for social science research, including confidentiality and data protection.

Conflict of interest

The authors declare that they have no competing financial interests, personal relationships, or institutional affiliations that could be perceived as influencing the research outcomes or interpretations.

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Figure I: Algorithm path

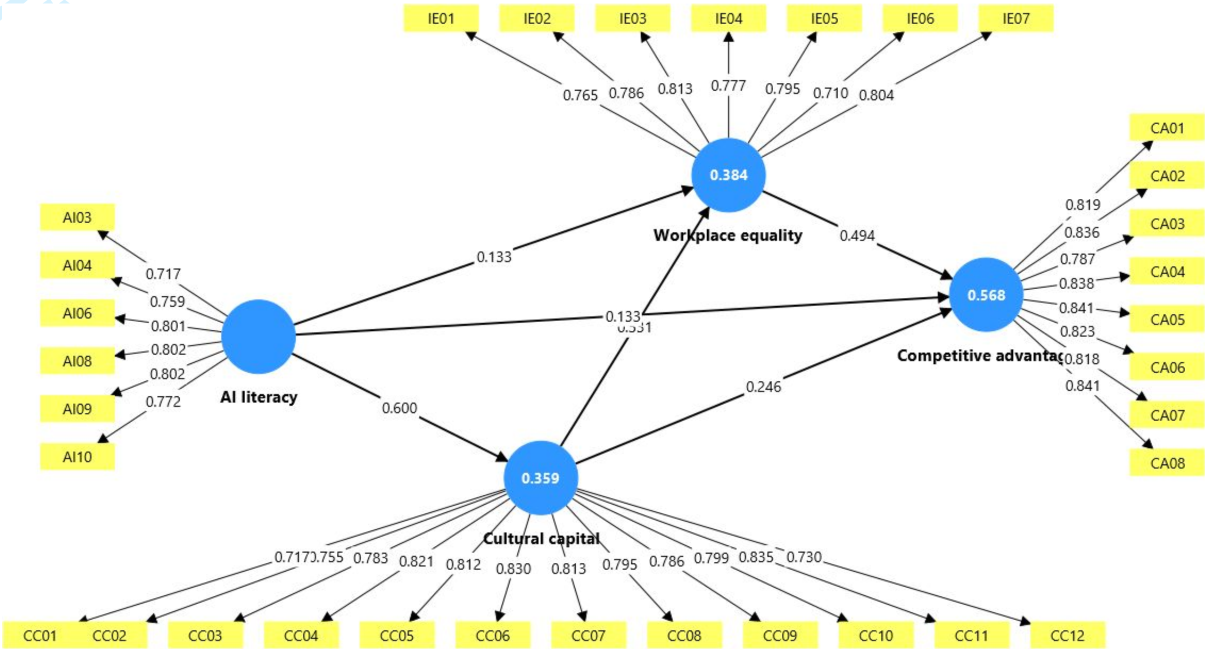

Table I. Construct reliability and outer loadings matrix

Measurements	Outer loadings	VIF	CA	CR	AVE
AI literacy	-	-	0.868	0.901	0.603
AI03: I can identify the AI technologies embedded in the applications I use.	0.717	1.526			
AI04. I effectively use AI applications to support my daily work.	0.759	1.965			
AI06 I use AI applications to improve my work efficiency.	0.801	2.212			
AI08: I select appropriate solutions from the options provided by smart agents.	0.802	2.049			
AI09: I can choose the most suitable AI application for a specific task.	0.802	2.157			
AI10:I consistently adhere to ethical principles when using AI applications.	0.772	1.839			
Competitive advantage	-	-	0.933	0.945	0.681
CA01. My organization performs better than its main competitors.	0.819	2.657			
CA02. My organization has a stronger competitive position than most competitors in the industry.	0.836	2.708			
CA03. Compared with competitors, my organization is more successful in achieving its strategic objectives.	0.788	2.342			
CA04. My organization offers products or services that are superior to those of competitors.	0.838	2.706			
CA05. My organization is more effective than competitors in responding to market changes.	0.841	2.779			
CA06. My organization creates greater value for customers than its competitors.	0.823	2.553			
CA07. My organization has capabilities that are difficult for competitors to imitate.	0.817	2.603			
CA08. Overall, my organization enjoys a sustainable advantage over its competitors.	0.841	2.848			

Psychological capital	-	-	0.945	0.952	0.625
CC01. I feel confident when presenting my work in meetings with management	0.717	2.124			
CC02. I can identify multiple ways to solve problems at work	0.755	2.647			
CC03. I am confident in my ability to master new job procedures.	0.783	2.610			
CC04. I stay focused on achieving my work goals.	0.821	3.197			
CC05. I pursue my work goals with energy and persistence.	0.812	3.175			
CC06. I can find alternative ways to achieve my goals when obstacles arise.	0.830	3.551			
CC07. I grow stronger after facing challenges at work.	0.813	3.126			
CC08. I feel prepared to face work difficulties based on past experiences.	0.795	2.438			
CC09. I recover quickly and move forward after work-related setbacks.	0.786	2.528			
CC10. I believe I will be successful in my job in the future.	0.799	3.122			
CC11. I focus on the positive aspects of work-related situations.	0.835	3.479			
CC12. I believe difficult situations at work will eventually improve.	0.730	2.192			
Workplace equality	-	-	0.892	0.915	0.607
IE01. I have a clearly defined level of influence over my work goals.	0.764	2.027			
IE02. I have a clearly defined role in workplace decision-making.	0.783	2.273			
IE03. I have fair opportunities for career development.	0.812	2.239			
IE04. I experience a fair level of job security.	0.777	2.080			
IE05. I receive fair benefits for my role.	0.797	2.295			
IE06. I receive fair compensation for my role.	0.712	1.668			
IE07. I am treated with respect at work.	0.806	2.224			

Table II. f-square

Constructs	AI literacy	Competitive advantage	Psychological capital	Equality at workplace
AI literacy		0.043	0.561	0.001
Competitive advantage				0.349
Psychological capital		0.284		0.076
Workplace equality				

Table III. Discriminant validity - HTMT

Constructs	AI literacy	Competitive advantage	Psychological capital	Equality at workplace
AI literacy				
Competitive advantage	0.554			
Psychological capital	0.651	0.666		
Workplace equality	0.503	0.770	0.661	

Table IV. Model fit

Model fit and quality indicators	Saturated model	Estimated model
Chi-square	1914.402	1914.402
NFI	0.833	0.833
SRMR	0.055	0.055
d_G	0.733	0.733
d_ULS	1.705	1.705

Table V. Bootstrapping hypotheses testing results

Path	Original sample (O)	Sample mean (M)	Standard deviation (STD)	T stat (|O/STD|)	P values
AI literacy -> Competitive advantage	0.133	0.133	0.048	2.761	0.006
AI literacy -> Cultural capital	0.600	0.602	0.037	16.026	0.000
AI literacy -> Workplace equality	0.133	0.131	0.057	2.349	0.019
Cultural capital -> Competitive advantage	0.246	0.247	0.065	3.756	0.000
Cultural capital -> Workplace equality	0.531	0.534	0.053	10.039	0.000
Workplace equality -> Competitive advantage	0.494	0.494	0.056	8.884	0.000

Table VI. Hypothesis description

Hypothesis		Results
H1	AI literacy → Competitive advantage. AI literacy confers a competitive advantage by equipping employees to deploy, evaluate, and strategically integrate AI, thereby strengthening dynamic capabilities that foster innovation and superior firm performance (Teece, 2018; Gama and Magistretti, 2025).	Support
H2	AI literacy → Workplace equality. AI literacy promotes workplace equality by enabling individuals and organizations to recognize algorithmic bias, govern AI responsibly, and ensure fair and inclusive workplace practices. This process helps reduce technology-driven inequality (Acker, 2006; Kellogg et al., 2020).	Support
H3	AI literacy → Psychological capital. AI literacy fosters psychological capital by strengthening self-efficacy, optimism, hope, and resilience by increasing employees' sense of control and competence when interacting with advanced technologies (Bandura, 1997; Luthans et al., 2007).	Support
H4	Psychological capital → Competitive advantage. Psychological capital contributes to competitive advantage by enhancing employees' motivation, learning, innovation, and adaptability, which, in turn, translate human strengths into sustained competitive advantage (Luthans et al., 2007; Wright et al., 2014).	Support
H5	Psychological capital → Workplace equality. Psychological capital improves workplace equality by empowering employees to engage constructively, voice concerns, and navigate structural inequalities, thereby enabling organizational policies to produce more equitable outcomes in practice (Avey et al., 2011; Healy et al., 2019).	Support
H6	Workplace equality → Competitive advantage. Workplace equality drives competitive advantage by fostering inclusive and equitable workplaces that broaden talent utilization, improve collaboration, and enhance innovation capacity, thereby reinforcing competitive advantage through socially embedded dynamic capabilities (Richard et al., 2013; Herlitah, 2025).	Support