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"Artificial Intelligence Literacy and Human Capital Development: Examining the Implications for Workforce Competence and Productivity in the Digital Economy"

Artificial Intelligence Literacy and Human Capital Development: Examining the Implications for Workforce Competence and Productivity in the Digital Economy

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Abstract

The digital economy has placed unprecedented demands on workers to understand, evaluate and apply artificial intelligence competently, making the readiness of the workforce, rather than the sophistication of the technology alone, the decisive factor in whether nations and organisations realise the productivity gains AI promises; it is this concern that prompted the this paper, Artificial Intelligence Literacy and Human Capital Development: Examining the Implications for Workforce Competence and Productivity in the Digital Economy. The paper specifically examine the extent to which AI literacy influences workforce competence, to assess the relationship between human capital development and productivity among workers exposed to AI technologies, and to determine the extent to which AI literacy and human capital development jointly account for variations in workforce productivity. The paper adopted Task-Based Model of Automation and Labour Demand theory as its theoretical anchor, and followed a qualitative library-based methodology, synthesising recent empirical and theoretical literature drawn from verifiable, peer-reviewed sources. The findings of the paper revealed that AI literacy significantly strengthens workforce competence, that human capital development substantially mediates the productivity effects of AI exposure, and that the two factors interact rather than operate independently, with productivity gains concentrated where both are jointly present. The paper concluded that artificial intelligence does not automatically raise workforce productivity but does so only where literacy and human capital development jointly enable workers to occupy the tasks that automation creates. It recommended deliberate, integrated investment in AI literacy training alongside broader human capital development programmes within organisations and national skills policy.

Keywords: Artificial Intelligence Literacy, Human Capital Development, Workforce Competence, Workforce Productivity, Digital Economy

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Introduction

The global economy has entered a phase in which artificial intelligence (AI) no longer occupies a narrow technical niche but has extended its reach into finance, health care, education, manufacturing and public administration. McKinsey estimates that generative AI alone could contribute between $2.6 trillion and $4.4 trillion annually to global output, while firms that have integrated AI into their operations report workforce performance gains of up to 40% (World Economic Forum, 2025). Such figures indicate that the value AI generates is not self-executing; it is realised only when workers possess the competence to interpret, question and apply algorithmic systems responsibly.

This condition has given rise to the concept of AI literacy, defined by Ng et al. (2021) as the set of competencies that enable individuals to critically evaluate, communicate with and employ AI technologies across educational, domestic and occupational settings. Ng, Luo, Chan and Chu (2024) refined this construct further by validating an instrument that measures AI literacy along affective, behavioural, cognitive and ethical dimensions, thereby confirming that literacy in this domain extends beyond technical operation to encompass judgement and ethical discernment.

Within human resource development scholarship, Li and Kim (2024) demonstrated that AI-related competencies cluster around skills, relevance, values and knowledge, and argued that organisations preparing their personnel for the AI era must treat literacy as a deliberate developmental outcome rather than an incidental by-product of exposure to new tools. This position aligns with classical human capital theory, which holds that investment in education, training and skill acquisition raises the productive capacity of labour and, by extension, national output.

Acemoglu (2025) revisited this proposition in the context of AI, cautioning that automation does not uniformly raise productivity; its benefits accrue chiefly to workers and firms able to complement algorithmic output with domain expertise. Tambe (2025) reached a comparable conclusion, showing that workers who combine domain knowledge with algorithmic literacy adapt more effectively to AI-augmented tasks than those who rely on either skill in isolation. Damioli, Van Roy, Vertesy and Vivarelli (2025) further established, using firm-level data, that AI adoption is associated with measurable productivity gains only where a technologically competent workforce is already present, confirming that human capital functions as a precondition for, rather than a consequence of, technological gain.

The implications of this relationship are especially pronounced for developing economies in Asia, Africa, Latin America and countries in the middle East. Das and Drine (2020) observed that Africa's distance from the technological frontier is sustained less by capital scarcity than by deficits in human capital and institutional readiness. More recently, the African Development Bank (2025) projected that inclusive deployment of AI could generate up to $1 trillion in additional gross domestic product for Africa by 2035, a figure equivalent to nearly one-third of the continent's current output, provided that labour is adequately skilled to absorb the technology.

Abolaji (2025) similarly argued that the pace at which African economies such as Nigeria, South Africa, Ghana and Kenya among others benefit from digital transformation depends substantially on the extent to which infrastructure and human capital deficits are addressed concurrently. For Nigeria, where digital transformation strategies increasingly reference AI as an engine of diversification, the adequacy of workforce preparation determines whether such technological adoption translates into genuine productivity or merely widens existing skill disparities.

Statement of the Problem

Despite the volume of policy attention devoted to AI adoption, a persistent gap exists between the pace at which AI technologies are introduced into workplaces and the pace at which the workforce acquires the literacy required to use them competently and productively. Organisations continue to invest in AI systems while devoting comparatively little structured attention to the competencies, ethical awareness and evaluative judgement that determine whether such systems are used responsibly and effectively (Li & Kim, 2024). This imbalance produces conditions under which technology is present but underutilised, or worse, misapplied in ways that generate bias, erode trust and compromise the quality of decision-making that AI was expected to improve (Zhang et al., 2025).

The problem is compounded in developing economies, where infrastructural constraints intersect with limited access to structured AI training. Evidence from African contexts indicates that automation can raise operational productivity substantially where human capital is adequately developed, yet the same evidence identifies human capital and governance deficits as the principal barriers preventing many firms from realising these gains (Das & Drine, 2020). It remains unclear, both theoretically and empirically, how AI literacy interacts with existing measures of human capital to produce workforce competence, and whether current training interventions are calibrated to close this gap rather than merely to familiarise workers with software tools.

Furthermore, much of the available scholarship addresses AI literacy either as an educational outcome confined to classrooms or as an organisational training metric, with comparatively limited attention paid to how literacy accumulated through either channel translates into measurable productivity within labour markets structured differently from those of advanced economies. Without a clearer understanding of this relationship, policies aimed at workforce digitalisation risk allocating resources toward technology procurement while underinvesting in the human capital foundations on which the productive use of that technology depends.

This paper is therefore concerned with examining how AI literacy shapes workforce competence and productivity within the digital economy, and with identifying the conditions under which

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human capital development translates AI adoption into genuine economic gain rather than superficial technological presence.

Aim and Objectives

The aim of this paper was to examine the implications of artificial intelligence literacy and human capital development for workforce competence and productivity within the digital economy.

Specific Objectives

The specific objectives of the study were to:

1. examine the extent to which artificial intelligence literacy influences workforce competence in the digital economy;
2. assess the relationship between human capital development and productivity among workers exposed to artificial intelligence technologies;
3. determine the extent to which artificial intelligence literacy and human capital development jointly account for variations in workforce productivity within the digital economy.

Literature Reviews

This section deals with conceptual review, empirical review and theoretical framework as follows:

Conceptual Review

The key concepts in this paper are reviewed as follows:

Artificial Intelligence Literacy

In conceptualising Artificial Intelligence Literacy, Ng et al (2021) submitted that the competencies that enable individuals to critically evaluate AI technologies, communicate and collaborate with such systems, and employ them as tools across educational, domestic and occupational settings, an account that positions literacy primarily as evaluative and applied competence rather than mere familiarity with software. Also, Ng et al. (2024) extended this position by validating an instrument that measures AI literacy along affective, behavioural, cognitive and ethical dimensions, thereby arguing that literacy also involves attitudinal and moral discernment and not technical operation alone.

In the other hand, Li and Kim (2024), writing from a human resource development standpoint, situated AI literacy within four competency clusters, namely skills, relevance, values and knowledge, and maintained that literacy is best understood as an organisationally cultivated capacity rather than an individual trait acquired incidentally. Where Ng et al. (2021) emphasise cognitive and ethical evaluation, Li and Kim (2024) foreground institutional cultivation, a distinction that matters for workplace contexts where competence is developed through structured training rather than self-directed exposure.

In this paper, AI literacy is adopted as the ability of workers to understand, critically evaluate, apply and ethically govern artificial intelligence tools within their occupational roles, following Li and Kim (2024).

Human Capital Development

In their own views, Mabaso and Ontong (2025) defined human capital development as the deliberate cultivation of knowledge, skills and competencies within a workforce, arguing that it functions as a catalyst for organisational resilience and national economic transformation rather than a passive outcome of formal education. Abrha and Weldeyohans (2025) approached the concept more broadly, treating human capital development as encompassing education, skill acquisition and health, and contending that strategic investment across these dimensions constitutes the foundation for sustained productivity and innovation.

The two positions differ in scope: Mabaso and Ontong (2025) confine their treatment to organisational and workforce-level cultivation, whereas Abrha and Weldeyohans (2025) situate the concept within a wider developmental economics framework that includes health and macroeconomic outcomes. For the purposes of this paper, human capital development is adopted, following Mabaso and Ontong (2025), as the deliberate process of building employees' knowledge, skills and competencies to strengthen organisational and economic performance, a definition suited to the workforce-centred focus of this enquiry.

Workforce Competence

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Shatalova (2023) defined workforce competence as the accumulated potential of labour to respond to structural and technological transformation, arguing that competence must be reconceptualised as digitalisation reshapes the tools and processes through which work is performed. This position treats competence as dynamic and continually reconstituted rather than fixed at the point of training.

A related but distinct emphasis appears in Rahmaningtyas, Joyoatmojo, Kristiani, Murwaningsih and Noviani (2023), who framed competence through the lens of competence-based learning, defining it as the alignment between acquired skills and the demands of employability in a changing labour market, thereby stressing outcome alignment over adaptive capacity. In all, Shatalova (2023) privileges adaptability under technological change, while Rahmaningtyas et al. (2023) privilege the fit between skill and job requirement.

This paper adopts Shatalova's (2023) formulation, defining workforce competence as the capacity of labour to adjust its skills and knowledge in response to the technological transformation of work, given the study's concern with AI as a transformative technology.

Workforce Productivity

Abdelwahed and Al Doghan (2023) defined workforce productivity as the measurable output that employees generate relative to the effort, time and resources expended in the course of their duties, and demonstrated empirically that engagement and organisational factors act as significant predictors of this outcome. Their treatment positions productivity as an outcome variable shaped jointly by individual disposition and organisational context rather than as a purely technical ratio of inputs to outputs.

This differs from more conventional economic renderings that reduce productivity to output per hour of labour without reference to psychological or organisational mediators. Because this study is concerned with how literacy and human capital shape workplace outcomes rather than purely macroeconomic output, the definition offered by Abdelwahed and Al Doghan (2023) is adopted, with workforce productivity understood as the measurable quantity and quality of output that employees produce within a given period, as shaped by their competencies and organisational conditions.

Digital Economy

Bukht and Heeks (2017) offered the most widely cited scholarly definition, distinguishing a narrow "digital sector" comprising information and communication technology production from a broader digital economy that includes all economic activity substantially dependent on digital technologies, a classification that continues to underpin recent empirical work (Budiarto & Nordin, 2024).

In his own submission, Yao (2023), described the digital economy instead as the ongoing industrial transformation driven collectively by artificial intelligence, big data, blockchain and automation, an emphasis on technological composition rather than sectoral boundaries. The distinction is consequential: Bukht and Heeks (2017) enable measurement through sectoral classification, whereas Yao (2023) treats the digital economy as an emergent technological era.

This paper therefore adopts Bukht and Heeks's (2017) definition, understanding the digital economy as economic activity that is substantially dependent on digital technologies, including artificial intelligence, for its production, distribution and exchange, since this framing accommodates measurable workforce-level analysis.

The Extent to Which Artificial Intelligence Literacy Influences Workforce Competence in the Digital Economy

Empirical evidence increasingly demonstrates that AI literacy shapes how effectively workers translate access to intelligent systems into functional competence. Lee and Jeon (2025), surveying 441 employees in South Korea, found that conscientiousness, openness, learning agility and organisational AI resource support each strengthened AI literacy, which in turn mediated improvements in job performance, indicating that literacy functions as the mechanism through which personal disposition and organisational investment convert into usable competence rather than as an independent outcome.

Liu et al. (2025), working with a sample of Chinese knowledge workers, constructed a five-dimensional Generative AI Literacy scale spanning technical competence, prompt optimisation, content evaluation, innovative application and ethical awareness, and reported a statistically significant effect of literacy on job performance ($\beta = 0.680$, $p < 0.001$), with creative self-efficacy partially mediating the relationship. This finding indicates that literacy operates not merely by teaching workers to operate software but by strengthening their belief in their own capacity to apply AI creatively to unfamiliar problems, a psychological dimension of competence that purely technical training programmes often overlook.

The clearest demonstration of how literacy conditions competence comes from field experiments rather than surveys. Dell'Acqua et al. (2023/2026), in a preregistered experiment involving 758 consultants at Boston Consulting Group, found that access to GPT-4 raised performance markedly for tasks within the model's competence frontier but degraded performance on tasks outside it, and that consultants who received a brief prompt-engineering orientation outperformed those with unguided access, showing that a modest increment in literacy altered whether AI assistance helped or harmed output quality. This "jagged frontier" finding is significant for workforce competence because it establishes that raw access to AI tools does not automatically confer competence; workers must learn to judge which tasks lie within the tool's reliable range, a discernment skill that is itself a component of literacy.

Brynjolfsson et al. (2025) corroborated this pattern in a naturalistic setting, examining 5,172 customer support agents at a Fortune 500 software firm and finding that access to a generative AI conversational assistant raised productivity, measured as issues resolved per hour, by 15% on average, with novice and lower-skilled agents improving by as much as 34%, effectively compressing the experience curve so that an agent with two months' tenure performed comparably to one with six months' tenure working unaided. The authors attributed this compression to the tool's capacity to disseminate the tacit practices of more competent workers to less experienced ones, which is functionally an accelerated literacy-transfer mechanism embedded within the technology itself.

From a human resource development perspective, Li and Kim (2024) argued that AI-related competence should be understood across four clusters, namely skills, relevance, values and knowledge, and maintained that organisations which treat AI literacy as a structured developmental programme produce more consistent competence gains than those relying on informal, self-directed exposure.

This is corroborated by workplace evidence from Nigeria, where Mago and Clinton (2025), examining Polaris Bank as a case study, found that AI-powered banking services improved operational efficiency but that the scale of improvement depended substantially on the technical proficiency of the staff operating and supervising the systems, reinforcing that AI literacy, rather than AI presence alone, determines whether workforce competence rises in step with technological adoption.

Arising from the above, this evidence indicates that AI literacy exerts a considerable and measurable influence on workforce competence, though the strength of that influence is conditioned by organisational support, task type and the deliberateness with which literacy is cultivated.

The Relationship Between Human Capital Development and Productivity Among Workers Exposed to Artificial Intelligence Technologies

Firm-level evidence from China provides some of the most rigorous documentation of how human capital development mediates the productivity effects of AI exposure. Luo, Lei and Hou (2024), using provincial panel data, found that AI technology innovation exerted a significant positive influence on total factor productivity, and that this effect operated substantially through the upgrading of human capital and industrial structure, with the productivity-enhancing effect of AI strengthening only in regions with higher levels of marketisation and digital infrastructure. This suggests that AI exposure alone is insufficient to raise productivity; the surrounding human capital environment determines whether the exposure translates into output gains.

Yu and Qi (2025), analysing enterprise-level data, reported that AI application raised enterprise productivity primarily by upgrading the human capital structure of the workforce, with the effect being more pronounced in firms that had already invested intensively in experienced, AI-capable personnel, indicating a complementarity between capital investment in AI and investment in people rather than a substitution of one for the other.

Cheng and Xu (2025), examining Chinese A-share manufacturing companies, similarly found that AI's contribution to what they termed new-quality productivity operated through an upgraded human capital structure, measured as the proportion of employees holding a bachelor's degree or higher, confirming that educational attainment functions as a channel through which AI-driven productivity gains are realised rather than a background characteristic incidental to the process.

Tambe (2025), studying reskilling initiatives across firms exposed to AI-driven workflow changes, found that workers who combined domain expertise with algorithmic literacy adapted to AI-augmented tasks more successfully than generalists possessing either skill in isolation, arguing that human capital investment focused narrowly on technical AI skills without complementary domain knowledge produced weaker productivity outcomes than investment that developed both simultaneously. This finding is consequential for policy because it implies that human capital development strategies emphasising generic AI training may underperform those tailored to specific occupational domains.

Mabaso and Ontong (2025), examining South African organisations navigating the Fourth Industrial Revolution, reported that firms which treated human capital development as a deliberate strategic function, rather than an ad hoc response to technological change, achieved more consistent productivity outcomes among employees working alongside automated and AI-supported systems, and identified leadership commitment and structured skills-development budgets as the strongest predictors of this consistency.

Complementary evidence from Nigeria's banking sector indicates that AI adoption improved operational efficiency and fraud detection accuracy most substantially in institutions with structured staff training programmes and stronger compliance environments, while microfinance and community banks lacking comparable investment in staff technical proficiency realised considerably smaller productivity gains from the same technology (Kayode & Feyisayo, 2025).

Collectively, this body of evidence indicates a consistent and mechanistically explained relationship: human capital development functions as the channel through which AI exposure is converted into measurable productivity, and its absence constrains or nullifies the productivity potential that AI technologies would otherwise offer.

The Extent to Which Artificial Intelligence Literacy and Human Capital Development Jointly Account for Variations in Workforce Productivity Within the Digital Economy

Although AI literacy and human capital development are frequently examined separately, several studies demonstrate that their combined presence explains substantially more variation in workforce productivity than either factor considered alone. Li and Kim (2024) argued explicitly that AI literacy should be embedded within broader human resource development architecture rather than treated as a standalone training module, contending that literacy programmes detached from wider human capital investment, such as career progression structures, mentoring and continuous learning culture, produce short-lived competence gains that fail to sustain productivity improvements over time. This theoretical position finds empirical support in Yu and Qi's (2025) enterprise-level analysis, which showed that the productivity benefit of AI application was strongest in firms exhibiting both a technically literate workforce and a structurally upgraded human capital base, an interaction effect indicating that literacy and human capital development are complementary rather than interchangeable determinants of productivity variation.

The Boston Consulting Group experiment conducted by Dell'Acqua et al. (2023/2026) offers a particularly precise illustration of this joint effect. Consultants who received both AI access and a short prompt-engineering orientation, representing an intervention combining a literacy component with a human-capital-style skills investment, produced work of measurably higher quality than those who received AI access without the orientation, even though both groups possessed identical underlying professional training. This demonstrates that literacy interventions can amplify the returns to pre-existing human capital, and conversely, that pre-existing human capital, in the form of consulting expertise, shaped how effectively the additional literacy training was absorbed and applied. A comparable pattern emerged in Brynjolfsson, Li and Raymond's (2025) customer service study, where the productivity gains from AI access were largest among workers with lower baseline tenure and skill, precisely the group for whom the AI tool most directly substituted for accumulated human capital by transmitting the practices of more experienced colleagues; among highly experienced agents, whose human capital was already extensive, AI access produced smaller productivity gains and occasionally slight declines in output quality, illustrating that the marginal contribution of AI literacy to productivity depends on the existing stock of human capital a worker brings to the task.

Practical evidence from manufacturing supports this joint explanatory pattern. Cheng and Xu (2025) found that AI's contribution to productivity in Chinese manufacturing firms operated through an interaction between algorithmic deployment and an upgraded human capital structure, such that firms with highly educated workforces translated AI adoption into productivity gains considerably more effectively than firms with comparable AI investment but lower average educational attainment among staff.

Similarly, in the Nigerian banking context, AI-driven credit and fraud-detection systems performed best in institutions combining structured data environments with sustained employee training, while institutions investing in AI infrastructure without corresponding investment in staff capability realised markedly smaller productivity returns, with credit recovery performance reaching 84.0% in well-resourced institutions compared with considerably lower rates elsewhere. This pattern indicates that productivity variation across firms and sectors within the digital economy is not adequately explained by AI literacy or human capital development independently, but by their joint presence, where literacy determines whether workers can operate AI systems competently and human capital development determines whether that competence is sustained, transferable and embedded within a broader capacity to apply judgement to AI-assisted work.

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Empirical Review

Lee and Jeon (2025) examined the effect of AI literacy and its antecedents on job performance in the context of South Korea. The study was conducted among corporate employees across various industries in South Korea. It was theoretically anchored in a mediation framework linking dispositional and organisational antecedents, namely personality traits, learning agility and organisational AI resource support, to work performance through the mediating mechanism of AI literacy, an approach broadly consistent with social cognitive reasoning that treats competence as a product of both individual and environmental inputs. The research adopted a quantitative, cross-sectional survey design. A sample of 441 employees was drawn through an online questionnaire administered across firms of varying size and sector, with structural equation modelling applied to test the hypothesised relationships. Data were collected using validated self-report scales measuring personality dimensions, learning agility, organisational support and job performance. The major findings showed that conscientiousness, openness, agreeableness, learning agility and organisational AI resource support each exerted a significant positive effect on AI literacy, and that AI literacy in turn significantly improved work performance, confirming its role as a mediating variable rather than a standalone predictor. The study concluded that organisations seeking to raise employee performance through AI adoption must simultaneously cultivate favourable personality-aligned recruitment, learning agility and structural resource support, since literacy alone, detached from these antecedents, is unlikely to develop.

This study is commendable for isolating the psychological and organisational precursors of AI literacy rather than treating literacy as an exogenous given, and its use of structural equation modelling strengthens the credibility of the mediation claim. However, the study was confined to a single national labour market with a comparatively high baseline of digital infrastructure, and it examined literacy as a mediator of individual job performance without extending the analysis to collective workforce productivity or to human capital development as a distinct organisational process. The present paper addressed this gap by situating AI literacy alongside human capital development as joint predictors of workforce productivity within a developing-economy digital economy context, an area Lee and Jeon's (2025) framework does not cover.

Dell'Acqua et al. (2026) examined the effects of artificial intelligence on knowledge worker productivity and quality by navigating what they termed the jagged technological frontier. The study was conducted at Boston Consulting Group, a global management consulting firm, and therefore situates itself within a high-skill professional services environment. Theoretically, the study introduced its own conceptual framework, the jagged technological frontier, which holds that AI capability boundaries are uneven across tasks of ostensibly similar difficulty, such that workers cannot rely on intuitive judgement alone to determine where AI assistance will help or harm performance. The research design was a preregistered randomised field experiment, considered one of the more rigorous designs available for establishing causal effect. A sample of

758 consultants, representing approximately 7% of the firm's individual-contributor-level consulting staff, was drawn using a stratified selection process from within the firm and randomly assigned to one of three conditions, namely no AI access, GPT-4 access, or GPT-4 access accompanied by a short prompt-engineering orientation. Data were collected through performance on realistic consulting tasks, subsequently scored by trained, blinded graders against predefined quality criteria. The major findings revealed that AI access substantially improved performance on tasks within the model's competence frontier but reduced performance on tasks lying outside it, and that consultants who received the brief prompt-engineering orientation, an incremental literacy intervention, achieved higher quality outcomes than those with unguided access. The study concluded that the productivity effects of AI are not uniform but depend on workers' capacity to judge which tasks fall within reliable machine competence, a judgement that can be improved through modest, targeted training.

This study is also commendable for its experimental rigour and its demonstration that literacy interventions, even brief ones, materially alter productivity and quality outcomes. However, the sample was restricted to elite, highly educated consultants in an advanced-economy professional services firm, limiting generalisability to lower-skill occupations or to firms in developing economies with weaker digital infrastructure, and the study did not examine human capital development as an antecedent condition shaping how workers absorbed the literacy intervention. The present study addresses this gap by extending the enquiry to a broader occupational base within a developing digital economy and by treating human capital development as a determinant that interacts with AI literacy, rather than holding it constant within a single elite professional population.

On the other hand, Yu and Qi (2025) examined whether AI application raises enterprise productivity, viewed specifically from the perspective of employee human capital upgrading. The study area comprised Chinese listed enterprises, drawing on firm-level data reflecting the broader diffusion of AI across the Chinese digital economy. The study was theoretically grounded in human capital theory and skill-biased technological change reasoning, which together propose that the productivity returns to new-generation technologies are contingent upon the quality and structure of the human capital available to absorb them. The research design was a quantitative panel-based empirical study using secondary data rather than primary survey instruments. The sample comprised several years of firm-year observations drawn from Chinese A-share listed companies, with firms selected through the researchers' construction of a text-based AI application index derived from corporate annual reports, supplemented by financial and workforce structure data obtained from established corporate databases. Data collection therefore relied on documentary and financial-statement analysis rather than questionnaires, with mediation and robustness tests, including instrumental variable estimation, applied to establish the human capital upgrading channel. The major findings indicated that AI application significantly raised enterprise productivity, and that this effect operated substantially through the upgrading of employee human capital structure, with the productivity benefit strongest in firms that had already invested intensively in experienced, technically capable personnel. The study concluded that AI and human capital investment function as complements rather than substitutes, such that enterprises pursuing AI adoption without corresponding investment in workforce human capital are unlikely to realise commensurate productivity gains.

This study tried for its large-sample, firm-level design and its use of robust econometric techniques to establish a causal channel rather than a mere correlation. However, its reliance on secondary financial and textual data meant that it could not capture individual-level AI literacy or the psychological and behavioural competencies through which workers actually engage with AI systems, and its context was confined to large, formally listed Chinese enterprises operating in a markedly different regulatory and infrastructural environment from Nigeria. The present paper addressed this gap by incorporating individual-level AI literacy alongside human capital development as joint explanatory variables, and by situating the enquiry within a developing-economy setting where firm formality, infrastructure and workforce composition differ substantially from the Chinese listed-enterprise context examined by Yu and Qi (2025).

Theoretical Framework

This paper was anchored on the theoretical framework of Task-Based Model of Automation and Labour Demand as reviewed below:

Task-Based Model of Automation and Labour Demand was propounded by Daron Acemoglu and Pascual Restrepo in 2018. The theory was developed to explain how new technologies, including robotics and, by extension, artificial intelligence, reshape the demand for labour by altering the allocation of tasks between workers and machines within the production process.

The theory's central assumption is that production can be decomposed into a range of discrete tasks, each of which may be performed either by human labour or by capital in the form of automated or intelligent systems, depending on their relative cost and capability at a given point in time. The theory further assumes that the introduction of a new technology produces two countervailing effects: a displacement effect, whereby tasks previously performed by workers are reassigned to machines, thereby reducing labour demand and, absent adaptation, potentially depressing productivity per worker; and a reinstatement effect, whereby the same technological change creates new tasks and roles that require human input, particularly tasks involving judgement, oversight, creativity and the management of the technology itself.

The theory further assumes that the net effect of automation on labour demand and productivity depends on the balance between these two forces, and that this balance is not fixed but is shaped by the extent to which the workforce possesses the skills and competencies required to move into the newly created tasks rather than being permanently displaced from the production process.

The strength of this theory lies in its capacity to explain both the disruptive and the complementary effects of technology within a single coherent framework, avoiding the oversimplification of treating automation as either wholly destructive or wholly beneficial to labour. It is also strong in its empirical tractability, having generated a substantial body of testable propositions and firm-level and industry-level evidence linking technology adoption to shifts in productivity, wages and employment structure, several of which were drawn upon in the empirical studies reviewed for this paper.

A further strength is its inherent flexibility, since the balance between displacement and reinstatement can be theorised as contingent upon workforce characteristics, allowing literacy and human capital development to be introduced as the moderating conditions that determine which of the two effects predominates in a given firm or economy.

The theory nonetheless carries notable weaknesses. It was formulated principally with reference to robotics and physical automation in advanced manufacturing economies, and its assumptions of rational, profit-maximising firms and comparatively frictionless labour reallocation sit uneasily with the structural and infrastructural constraints characteristic of developing economies such as Nigeria, where skills mismatches, weak digital infrastructure and limited institutional support can prevent the reinstatement effect from materialising even where new tasks theoretically exist. The theory is also limited in that it does not explicitly incorporate the psychological and behavioural dimensions of technology adoption, such as confidence, trust and perceived self-efficacy in using AI systems, that more recent literacy-focused research has shown to influence whether workers actually take up the new tasks available to them.

Applied to this study, artificial intelligence is understood as a task-augmenting and task-displacing technology whose net effect on workforce productivity in the digital economy depends on whether displaced tasks are offset by the creation of new, AI-complementary tasks that workers are equipped to perform. Within this framework, AI literacy functions as the enabling competence through which workers recognise, access and perform the newly created tasks generated by AI adoption, while human capital development functions as the sustained organisational and educational process through which such competence is built, maintained and renewed over time. Where both AI literacy and human capital development are weak, the theory predicts that the displacement effect will dominate, workers will be pushed out of automatable tasks without a corresponding movement into complementary ones, and workforce productivity will stagnate or decline despite technological investment.

Where AI literacy and human capital development are strong, the reinstatement effect is expected to dominate, enabling workers to move into oversight, evaluative and creative tasks that AI cannot perform unaided, thereby raising workforce competence and productivity in tandem with technological adoption. This theoretical logic directly underpins the objectives of the present study, providing the rationale for examining AI literacy and human capital development not as isolated variables but as joint determinants of the extent to which Nigeria's digital economy realises productivity gains from artificial intelligence rather than merely absorbing its disruptive effects.

Methodology

This paper adopted a qualitative library-based research design, relying on a narrative and thematic review of existing scholarly literature rather than primary data collection, an approach considered appropriate for conceptual and theory-building enquiries that seek to synthesise dispersed empirical findings into a coherent explanatory account (Snyder, 2019). The review drew principally on peer-reviewed journal articles, working papers from recognised research institutions, and preregistered field experiments published between 2018 and 2026, with particular emphasis placed on studies published within the most recent three years to ensure that the analysis reflected the current state of knowledge on artificial intelligence literacy, human capital development and workforce productivity within the digital economy, consistent with the recency criterion recommended for reviews of fast-evolving technological subject areas (Xiao & Watson, 2019).

Sources were identified through targeted searches of academic databases and repositories, including Scopus-indexed journals, Web of Science, ScienceDirect, SSRN and institutional repositories such as the National Bureau of Economic Research and the Harvard Business School working paper series, using combinations of key terms drawn directly from the study's objectives and conceptual variables. Studies were selected for inclusion on the basis of four criteria, namely their direct relevance to the concepts and objectives under investigation, the traceability and verifiability of their authorship and publication details, the use of an identifiable empirical or theoretical methodology rather than opinion-based commentary, and their contribution to explaining the relationship between artificial intelligence, human capital and productivity outcomes, a set of inclusion standards broadly consistent with established guidance for conducting rigorous narrative literature reviews (Grant & Booth, 2009).

Data extraction from each selected study focused on the theoretical framework employed, the research design and sample characteristics, the principal findings, and the extent to which the study addressed or left unaddressed the specific concerns of the present paper, after which the extracted material was synthesised thematically around the paper's stated objectives rather than presented as an unstructured accumulation of summaries, thereby allowing the reviewed evidence to be interrogated critically and integrated into the theoretical framework adopted for the study.

Discussion

The discussion of this paper is organised around the three objectives that guided it, namely the extent to which AI literacy influences workforce competence, the relationship between human capital development and productivity among AI-exposed workers, and the extent to which the two factors jointly account for variations in workforce productivity within the digital economy, and it interrogates the positions advanced by the authors reviewed in light of the Task-Based Model of Automation and Labour Demand.

On the first objective, the evidence reviewed converges on the position that AI literacy exerts a measurable and mechanistically explicable effect on workforce competence, though the studies differ in how directly they attribute this effect to literacy as opposed to organisational or contextual conditions. Lee and Jeon (2025) treated literacy as a mediating variable between personality and organisational support on one hand and job performance on the other, a framing that positions literacy as the conduit through which favourable dispositions and resources become productive competence rather than as a self-generating trait.

This is a defensible position, yet it invites scrutiny: if literacy is merely a pass-through mechanism, the practical policy implication would be to invest in personality-based recruitment and organisational support rather than in literacy training itself, a conclusion the authors do not draw explicitly but which their model implies. Dell'Acqua et al. (2026) offer a more direct causal demonstration, showing that even a brief prompt-engineering orientation altered whether AI assistance improved or degraded consultants' output, which suggests that literacy is not merely a symptom of prior advantage but an independently manipulable input capable of shifting competence outcomes within a matter of hours.

Reading these two studies together indicates that literacy operates on at least two levels, a slower dispositional and organisational layer described by Lee and Jeon, and a faster, task-specific skill layer demonstrated by Dell'Acqua and colleagues, both of which are compatible with the reinstatement mechanism proposed by Acemoglu and Restrepo (2018), since literacy in either form is what allows a worker to move into the new, AI-complementary tasks that automation creates rather than being confined to the tasks automation removes.

On the second objective, the reviewed evidence supports a relationship between human capital development and productivity among AI-exposed workers, but the mechanism identified by Yu and Qi (2025) is structural rather than psychological: productivity gains from AI application were strongest in enterprises that had already invested in an upgraded, more educated workforce, implying that human capital functions as a precondition that determines whether a firm can absorb AI-driven task reallocation at all. This finding sits in productive tension with the individual-level literacy findings above. Where Lee and Jeon (2025) and Dell'Acqua et al. (2026) examine how literacy changes what a given worker can do with AI, Yu and Qi (2025) examine how the aggregate human capital composition of a firm determines whether AI investment translates into productivity at the enterprise level at all.

This distinction matters practically: a Nigerian bank, for instance, may train individual staff in AI-assisted fraud detection, yet if the wider workforce lacks the educational base to interpret and act on the system's outputs, enterprise-level productivity gains identified in the Nigerian banking case studies reviewed earlier are unlikely to materialise, precisely the pattern observed where AI adoption improved credit recovery most strongly in institutions with structured, sustained staff training. This corroborates the theoretical framework's assumption that the reinstatement effect is not automatic but conditional upon the workforce's underlying capacity to absorb newly created tasks.

On the third objective, concerning the joint effect of AI literacy and human capital development on productivity variation, the reviewed studies, taken collectively, support an interaction rather than an additive relationship. Yu and Qi's (2025) finding that AI's productivity benefit was strongest where human capital upgrading and AI application coexisted, and Brynjolfsson, Li and Raymond's (2025) finding that productivity gains from AI access were largest among lower-tenure workers precisely because AI substituted for their comparatively thin human capital, together indicate that literacy and human capital development do not operate independently but condition one another's returns. Where human capital is already extensive, as among the most experienced customer support agents in Brynjolfsson et al.'s study, additional AI literacy produced only marginal gains and occasionally slight quality declines, whereas where human capital was limited, literacy-enabled AI access produced substantial gains.

This pattern is precisely what the Task-Based Model would predict once literacy and human capital are introduced as joint moderators of the displacement–reinstatement balance: workers with strong human capital already occupy tasks resistant to displacement, so AI chiefly assists at the margin, while workers with weaker human capital are more exposed to displacement and therefore benefit disproportionately when literacy allows them to move into reinstated, AI-complementary tasks.

These findings was supported by Task-Based Model of Automation and Labour Demand because it provides a coherent explanatory structure for the findings reviewed. The model's displacement effect accounts for the productivity losses or stagnation observed where literacy and human capital were weak, its reinstatement effect accounts for the productivity gains observed where both were strong, and its assumption that the balance between the two is conditional rather than fixed accounts for the heterogeneity of effects reported across the South Korean, Chinese, American and Nigerian contexts reviewed.

The findings thus affirm the theoretical premise that artificial intelligence does not produce a uniform effect on workforce productivity in the digital economy, but one whose direction and magnitude are substantially determined by the extent to which AI literacy and human capital development jointly equip workers to occupy the tasks that automation creates rather than merely displacing them from the tasks it removes.

Conclusion

This paper examined the extent to which artificial intelligence literacy influences workforce competence, the relationship between human capital development and productivity among workers exposed to AI technologies, and the extent to which the two factors jointly account for variations in workforce productivity within the digital economy. The paper therefore concluded that artificial intelligence does not raise workforce productivity automatically; it does so only where deliberate investment ensures that workers are both technically literate in AI and broadly equipped with the human capital needed to occupy the new tasks that automation creates.

Recommendations

Sequel to the above findings, the following recommendations were proposed:

1. Organisations should institute structured, role-specific AI literacy training programmes, rather than relying on informal or self-directed exposure, so that employees develop the evaluative judgement needed to use AI tools competently within their specific occupational tasks.
2. Employers of labour and policymakers should treat human capital development, particularly education, continuous skills upgrading and domain expertise, as a precondition for AI investment rather than an afterthought, ensuring that technology adoption is matched by corresponding investment in the workforce capable of absorbing it.
3. Organisations should design AI adoption strategies that integrate literacy training and human capital development as a combined intervention rather than as separate initiatives, since the evidence indicates that productivity gains are strongest where both factors are cultivated jointly and weakest where either is pursued alone.

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