

How Does Workplace AI Competence Shape the Work Performance of Young Workers in Vietnam? An Integrative Framework and Policy Implications

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Abstract

The rapid spread of artificial intelligence (AI), especially generative AI, is changing how tasks are carried out, how workers learn and how work performance is judged. However, access to AI does not automatically lead to higher productivity. The outcome depends on whether workers can understand the limits of AI, give clear instructions, integrate AI into their workflows, verify outputs, protect data and keep meaningful human control. This study develops an integrative framework that explains how workplace AI competence affects the work performance of young workers in Vietnam. The framework draws on human capital theory and the task-based approach, task-technology fit theory and the automation-augmentation paradox. Methodologically, the study combines a structured integrative literature review, an analysis of legal and policy documents, and official secondary labour market data for the period from 2021 to the first half of 2026. International experimental evidence shows that generative AI can reduce task completion time, improve output quality and raise productivity in many knowledge tasks, but these gains weaken or even reverse when tasks lie outside the capability frontier of the technology or when users lack verification skills. In Vietnam, the youth (15-24) unemployment rate increased from 7.63% in 2023 to 8.64% in 2025 and 8.77% in the first half of 2026, while the share of workers holding formal training qualifications continued to rise, which signals growing skill-transition pressure. At the same time, Vietnam's legal framework for AI expanded very quickly in 2025-2026. We propose a six-dimension workplace AI competence framework, six testable propositions and a policy package supported by a three-tier system of key performance indicators (KPIs). The paper offers a conceptual model that can be tested in future empirical studies of young Vietnamese workers.

Keywords: AI competence; AI literacy; work performance; young workers; human-AI collaboration; task-technology fit; Vietnam.

1. Introduction

Artificial intelligence (AI) has moved from being a specialised technology to a general-purpose tool that can take part directly in writing, data analysis, programming, customer service, design, research and decision support. Earlier waves of computerisation mainly replaced routine manual and clerical tasks while complementing non-routine analytical work (Autor et al., 2003). Generative AI is different because it also affects language-based and knowledge-intensive tasks that used to be seen as the comparative advantage of educated workers (Eloundou et al., 2024). The early empirical evidence is striking. In a randomised experiment with 453 college-educated professionals, Noy and Zhang (2023) found that access to ChatGPT reduced the time needed to complete mid-level professional writing tasks by about 40% and raised output quality by about 18%. In a large field setting, Brynjolfsson et al. (2025) followed 5,172 customer-support agents and found that an AI

assistant increased productivity, measured as issues resolved per hour, by 15% on average, with the largest gains among less experienced and lower-skilled workers. These results suggest that the value of AI depends less on whether a firm “has AI” and more on whether its workers can turn AI into a measurable, complementary capability.

However, it would be a mistake to treat “using AI” as the same thing as “performing better”. AI can produce answers that look convincing but are factually wrong; it can increase speed while reducing accuracy; and it can weaken professional judgement if users hand over too much of their thinking to the system. Dell’Acqua et al. (2023) describe this situation as a “jagged technological frontier”: the same AI model can perform very well on some tasks but fail on other tasks that look similar. In their field experiment with 758 consultants at Boston Consulting Group, consultants who used AI on tasks inside the frontier completed 12.2% more tasks, worked 25.1% faster and produced results of more than 40% higher quality than a control group. On a task deliberately chosen to lie outside the frontier, however, AI users were 19 percentage points less likely to reach a correct solution. For this reason, the key variable to study is not how often people use AI but their workplace AI competence, that is, the combination of knowledge, operational skills, evaluation ability, workflow redesign ability and responsible conduct that allows a worker to achieve better results without sacrificing quality, legal compliance or human control.

This issue is especially important for young workers. People at the beginning of their careers are usually highly exposed to digital technology, learn new tools quickly and are less attached to old routines. At the same time, they have less domain experience, tacit knowledge and situational judgement than senior colleagues. Young workers may therefore gain the most from AI, but they are also more exposed to risks such as over-reliance, undetected errors and the loss of the entry-level tasks through which professional skills are normally built. The OECD (2023) reports that skill shortages are one of the main barriers to AI adoption in firms and that training is needed not only for low-skilled workers but also for high-skilled workers and managers. At the global level, Gmyrek et al. (2025) estimate that about one in four workers is employed in an occupation with some exposure to generative AI, yet they conclude that the transformation of jobs, rather than their full replacement, is the most likely outcome because most occupations still require human input and oversight. Employers also expect fast skill change: according to the World Economic Forum (2025), 39% of workers’ core skills are expected to change by 2030, and AI and big data are the fastest-growing skills.

In Vietnam, the period 2021-2026 saw very fast institutional change. The first National Strategy on AI was issued in 2021 (Prime Minister of Vietnam [PM], 2021), and Resolution No. 57-NQ/TW of December 2024 made science, technology, innovation and digital transformation the key drivers of national development (Politburo of the Communist Party of Vietnam [Politburo], 2024). In 2025-2026, a new layer of institutions was added, including special pilot mechanisms for innovation (Government of Vietnam [GoV], 2025; National Assembly of Vietnam [NA], 2025e), the Law on Science, Technology and Innovation (NA, 2025b), a new Law on Employment (NA, 2025d), the Law on Personal

Data Protection (NA, 2025a) and, most importantly, the Law on Artificial Intelligence, in force since 1 March 2026 (NA, 2025c), with Decree No. 142/2026/ND-CP guiding its implementation (GoV, 2026). In August 2026, the Prime Minister also approved a National Programme for AI Human Resource Development (PM, 2026b) and a new National Strategy on AI to 2030, which replaced the 2021 strategy (PM, 2026c). As a result, the AI competence of workers is no longer only a voluntary technical skill; it is increasingly tied to obligations of risk management, transparency, accountability and human oversight.

Evidence for Vietnam, however, is still limited and fragmented. Do et al. (2026) developed and validated a 26-item AI literacy scale for Vietnamese university students with three dimensions: understanding, application, and ethics and responsibility. This is an important step for measurement, but the scale targets students rather than workers and is not linked to work performance. Meanwhile, recent international studies have begun to connect AI competence with job outcomes. Tan et al. (2026) show that task-technology fit is the main mechanism linking collaborative AI literacy to employee performance, while Naveed et al. (2026) find that AI literacy is positively associated with the work performance of university academics, partly through work engagement. There is therefore a clear research gap: no integrative framework yet explains how AI competence, human-AI coordination, organisational conditions, risks and the new legal environment jointly shape the work performance of young Vietnamese workers.

To address this gap, the study asks four research questions: (1) What components should make up the workplace AI competence of young workers in the context of generative AI and responsible AI governance? (2) Through which mechanisms can this competence improve, or reduce, work performance? (3) What conditions, pressures and gaps in Vietnam's labour market during 2021-2026 are relevant to the capacity of young workers to absorb AI? (4) Which policies and governance arrangements can turn AI competence into productivity, quality and adaptability, rather than simply increasing the intensity of tool use?

The paper makes three contributions. Theoretically, it extends the concept of "AI literacy" into "workplace AI competence" with six dimensions: understanding AI and its limits; interaction design; workflow integration; evaluation and verification; ethical, legal and data governance; and human-AI coordination with self-directed learning. In terms of mechanisms, it argues that the effect of AI competence on performance is conditional rather than linear, and depends on task-technology fit, organisational governance, foundational domain skills and the position of each task relative to the capability frontier of AI. Practically, it places this framework within Vietnam's new AI institutions and proposes solutions that link skill development with risk management, controlled testing and outcome-based KPIs. Section 2 reviews the literature and builds the conceptual model; Section 3 describes the methodology; Section 4 presents the findings; Section 5 discusses policy implications; and Section 6 concludes.

2. Literature Review and Theoretical Framework

2.1. Workplace AI competence: concept and dimensions

Early research on “AI literacy” focused on the extent to which individuals can recognise, understand, use and evaluate AI. Long and Magerko (2020) proposed a set of competencies that includes recognising AI, understanding how AI systems work, evaluating their outputs and considering ethical issues. In an exploratory review, Ng et al. (2021) confirmed that AI literacy is broader than technical skill and covers knowing and understanding AI, using and applying AI, evaluating and creating with AI, and AI ethics. Later studies moved from educational concepts to measuring user competence. Wang et al. (2023) developed an AI literacy scale with four dimensions: awareness, usage, evaluation and ethics. Carolus et al. (2023) added psychological components such as AI self-efficacy and self-management, and Laupichler et al. (2023) proposed a scale for non-experts built around technical understanding, critical appraisal and practical application. Taken together, these studies show that AI competence is a multidimensional construct that is different from general digital skills. At the policy level, Vietnam’s Digital Competence Framework for learners, issued in 2025, includes “application of artificial intelligence” as one of its six domains, with a focus on understanding, using and evaluating AI tools in an ethical way (Ministry of Education and Training [MOET], 2025). This confirms that AI competence is now recognised in national policy, although the framework is designed for learners rather than for workers.

In the workplace, the concept needs to go further than “knowing how to use a tool”. In this study, *workplace AI competence* is defined as a worker’s ability to purposefully combine knowledge of AI, interaction skills, domain expertise, evaluation skills and responsible norms in order to select, configure, use, verify and coordinate with AI systems, so that work goals are achieved with higher productivity, quality, creativity and reliability, while legal, ethical, data-related and de-skilling risks are kept under control. This definition differs from AI literacy in the educational sense in three ways. First, the unit of analysis is the task and the workflow rather than general knowledge. Second, the outcome is assessed through performance and risk rather than through a competence score alone. Third, the competence includes the ability to decide *when not to use AI*, which is an essential element of responsible practice.

Based on the international scales and the Vietnamese context, we propose six components. (i) *Understanding AI and its limits*: knowing what kind of data AI learns from, its probabilistic logic, and the possibility of bias, hallucination and outdated information, as well as the difference between prediction and verified knowledge. (ii) *Interaction design*: turning a goal into a clear request by giving context, constraints, examples and evaluation criteria, and breaking a complex task into smaller steps. (iii) *Workflow integration*: identifying which steps can be automated, which steps can be augmented and which steps must remain under human decision. (iv) *Evaluation and verification*: checking sources, logic and numbers, testing outputs, detecting errors and judging how reliable a result is. (v) *Ethical, legal and data governance*: protecting confidential and personal data,

respecting intellectual property, and ensuring fairness and transparency. (vi) *Human-AI coordination and self-directed learning*: assigning suitable roles to humans and AI, keeping one's own professional judgement, reflecting on practice and updating skills as the technology changes.

This structure builds on earlier work but also extends it. The student scale of Do et al. (2026) shows that AI competence can be measured reliably in Vietnam, but the workplace requires two additional layers: integrating AI into real workflows, and allocating decision rights between humans and AI. These two layers largely determine whether AI creates useful output or simply generates “more content that needs checking”. If future studies measure only self-confidence or frequency of AI use, the risk of construct bias will therefore be high. A heavy user may in fact be dependent on AI, whereas a highly competent worker may deliberately avoid AI for sensitive tasks or for tasks outside the capability frontier of the technology.

2.2. Work performance in the AI era

Work performance is a broader construct than productivity alone. Koopmans et al. (2013) developed the Individual Work Performance Questionnaire based on a framework that distinguishes task performance, contextual performance, adaptive performance and counterproductive work behaviour. A multidimensional approach is even more necessary in the AI era, because AI can improve speed while increasing errors, raise the quality of individual output while weakening team coordination, or help solve today's task while eroding long-term capability. This study therefore conceptualises the work performance of young workers through five groups of outcomes: (1) *productivity*, including time, output volume and cost; (2) *quality*, including accuracy, completeness and consistency; (3) *creativity and problem solving*; (4) *adaptability and learning*; and (5) *collaboration and compliance*. This approach allows both the direct benefits and the hidden costs of AI to be observed.

We also distinguish between *immediate output performance* and *sustainable performance*. If AI helps a person write faster but weakens his or her ability to analyse independently, the organisation gains in the short run but bears a capability cost in the long run; when AI is used as a critical partner, however, workers may increase output and learn faster at the same time. The finding of Brynjolfsson et al. (2025) that less experienced workers gained the most suggests such a learning mechanism: AI can turn part of the practical know-how of top performers into real-time support for newcomers. Work performance in the AI era should therefore be assessed along two axes: the value of current output, and the maintenance and development of human capability.

2.3. Integrative theoretical foundations

Human capital theory and the task-based approach provide the first foundation. According to Becker (1993), investment in education, training and knowledge increases the productive capacity of individuals. In the AI context, AI competence can be seen as a form of technology-specific human capital. The return on this capital, however, is not uniform: the same AI skill may create high value in information-intensive jobs but little

value in tasks that are not yet digitised, and its return depends on the worker's underlying domain knowledge. The task-based approach adds a useful perspective. Autor et al. (2003) show that technology substitutes for tasks that can be codified and complements tasks that require problem solving and judgement, while Acemoglu and Restrepo (2019) argue that automation displaces labour from some tasks but can also reinstate labour by creating new tasks. For young workers, generative AI may take over some entry-level tasks such as drafting, summarising or searching for information, but it also creates new tasks such as specifying requests, checking outputs and integrating results into decisions. Workplace AI competence is precisely the human capital needed to perform these new tasks. Domain knowledge remains necessary to ask the right questions, detect errors, judge plausibility and take final responsibility. A skill strategy that focuses only on operating tools and ignores domain knowledge may therefore create “hollow AI capital”, that is, fast use of AI that rarely produces reliable value.

Task-technology fit (TTF) theory provides the second foundation. Goodhue and Thompson (1995) argue that technology improves individual performance only when its functions match the requirements of the task and when users actually use it. For generative AI, this fit is dynamic, because model capabilities change quickly and the boundary between suitable and unsuitable tasks is hard to observe. AI competence therefore works as a “fit-diagnosis” mechanism: a competent worker not only knows how to use AI but also knows which tasks should be assigned to AI, what level of automation is acceptable and how much verification is required. Tan et al. (2026) provide new evidence for this mechanism. Using data from 403 employee-supervisor dyads collected in two waves, they find that collaborative AI literacy improves employee performance mainly by strengthening task-technology fit, and that high technostress weakens this pathway.

The third foundation is the *automation-augmentation paradox*. Raisch and Krakowski (2021) argue that automation and augmentation are not mutually exclusive strategies; they depend on each other and create tensions within organisations. When AI automates routine work, the human role shifts towards setting goals, handling exceptions, evaluating, creating and taking responsibility. The human-AI symbiosis view of Jarrahi (2018) similarly stresses that AI is strong in processing data and recognising patterns, while humans keep an advantage in intuition, contextual judgement and dealing with ambiguity. It follows that work performance cannot be optimised by the goal “let AI do as much as possible”. The optimum lies in designing a coordination structure in which AI is given the tasks where it has a comparative advantage and humans focus on tasks that require judgement and accountability.

Recent experimental evidence supports this coordination view. Dell'Acqua et al. (2026) found that professionals working individually with AI produced solutions of similar quality to two-person teams without AI, and that AI helped commercial and research-and-development staff move beyond their functional “silos”. These results imply that AI competence has two functions at the same time: it expands cognitive capacity, and it reorganises the boundaries of expertise. For young workers, AI can lower the cost of

accessing knowledge and speed up on-the-job learning, but only if organisations design feedback, verification and mentoring mechanisms instead of allowing the tool to replace the process through which skills are formed.

2.4. Conceptual model and research propositions

Based on the three foundations, we propose a sequential model: AI competence → quality of AI use and human-AI coordination → task-technology fit and job redesign → work performance. Organisational support, the quality of AI governance, foundational domain skills and task complexity act as moderators. At the same time, there is a negative risk channel: low competence combined with intensive use may lead to automation bias, misinformation, data breaches, extra checking work and de-skilling. In other words, the relationship between the *intensity* of AI use and performance may be non-linear, and AI competence is what turns experimental use into productive capability. Table 1 summarises the six propositions.

Table 1. *Research propositions of the conceptual model*

Proposition	Statement	Main mechanism
P1	Workplace AI competence is positively related to work performance, other things being equal.	Faster processing, better output quality and a wider capacity for problem solving.
P2	Task-technology fit mediates the relationship between AI competence and work performance.	Competence helps workers choose the right tasks, tools and level of automation.
P3	The quality of human-AI coordination mediates the relationship between AI competence and work performance.	Role allocation, critical questioning, verification and retained human decision rights.
P4	Organisational support and AI governance positively moderate the competence-performance relationship.	Training, approved tools, data, procedures and accountability.
P5	Task complexity and the position of the task relative to the AI capability frontier moderate the relationship.	High gains for tasks inside the frontier; rising risk for tasks outside it.
P6	High-intensity AI use combined with low verification competence reduces sustainable performance.	Errors, over-reliance, de-skilling, correction costs and compliance risks.

Note. Propositions are stated for future empirical testing; they are not tested in this study.
Source: Developed by the authors.

The model addresses two limitations of many earlier studies. First, it separates competence from intensity of use, so that a heavy user is not automatically assumed to be a competent user. Second, it widens the dependent variable from short-term productivity to quality, adaptability, collaboration and compliance. This conditional approach is consistent with the international evidence, which shows clear gains for well-suited tasks (Brynjolfsson et al., 2025; Noy & Zhang, 2023) but very different results for tasks outside the capability frontier (Dell’Acqua et al., 2023). Research on young Vietnamese workers should therefore measure AI competence, task-technology fit, organisational support and verification quality together, in order to avoid simplistic conclusions about the effect of AI.

3. Research Methodology

The study uses a conceptual and policy-oriented research design based on a structured integrative literature review combined with the analysis of secondary data. An integrative review is appropriate when the aim is to combine insights from different fields in order to build a new conceptual framework, rather than to estimate a pooled effect size (Snyder, 2019). This is not a primary survey, and it does not estimate causal coefficients for young Vietnamese workers. This choice reflects the current state of the evidence: Vietnam does not yet have a nationally representative dataset that measures AI competence, task characteristics, organisational conditions and work performance at the same time. Instead of producing assumed figures, the study combines three layers of evidence: (i) peer-reviewed academic research and reports of international organisations on AI competence, human-AI collaboration and work performance; (ii) official labour market statistics for Vietnam; and (iii) legal, strategic and policy documents related to AI, innovation, employment and youth. Labour market indicators cover the period 2021-2026. Because the cut-off date of this manuscript is 28 September 2026, the latest official release covers the second quarter and the first half of 2026; third-quarter statistics had not yet been published. For policy documents, the study includes all documents that had been issued and could be verified by 28 September 2026, among them Decision No. 1528/QĐ-TTg of 11 August 2026 and Decision No. 1671/QĐ-TTg of 28 August 2026 (PM, 2026b, 2026c).

3.1. Data sources and selection criteria

Academic sources were identified mainly through Scopus, Web of Science and Google Scholar, with priority given to peer-reviewed journals of international standing (for example, *Science*, *The Quarterly Journal of Economics*, *Academy of Management Review*, *Organization Science* and *MIS Quarterly*) and to publications of the OECD, the International Labour Organization (ILO) and the World Economic Forum. A source was included if it served at least one of four roles: (a) defining the concept or measurement of AI competence; (b) providing an explanatory theory; (c) providing empirical evidence on productivity or work performance; or (d) analysing the effects of AI on the labour market. Sources that were purely journalistic, lacked a clear method or could not be traced to an original were not used as main evidence. Because the aim was conceptual integration rather than a systematic review, a full PRISMA protocol was not applied; this is acknowledged as a limitation in Section 6. For Vietnam, labour statistics were taken only from the official

press releases on the labour force survey published by the General Statistics Office of Vietnam (GSO) and, since its restructuring in 2025, by the National Statistics Office of Vietnam (NSO) under the Ministry of Finance. Legal and policy documents were checked against the Government's legal document portal and the Official Gazette. The final reference base consists of 24 academic and international-organisation sources, 17 legal and policy documents and 6 official statistical releases.

3.2. Analytical procedure

The analysis followed four steps. In step one, the selected studies were coded into five groups: components of AI competence, mechanisms of influence, performance indicators, conditioning variables and risks. In step two, the measurement frameworks were compared in order to build a six-component structure suitable for the workplace. In step three, the Vietnamese labour market series were compiled and interpreted as *contextual indicators*; they were not used to infer the causal effect of AI. Three rules were applied to ensure consistency: (a) each value is reported as first published in the relevant annual release, because the statistical office sometimes revises earlier estimates in later releases; (b) 2026 values are reported separately because they are not fully comparable with annual averages; and (c) the youth-to-working-age unemployment ratio was calculated by the authors as the youth (15-24) unemployment rate divided by the working-age unemployment rate. In step four, the institutional analysis followed the logic of objectives → instruments → mechanisms → actors → resources → KPIs → risks, in order to assess how well the legal framework for AI fits the need to develop workers' competence. Source triangulation was applied throughout: an important policy argument was used only when the original official document was available, and a conclusion about AI productivity was stated only within the sample and design of the original study.

4. Findings

4.1. The youth labour market and skill-transition pressure, 2021- 2026

Vietnam's labour market recovered strongly after the COVID-19 shock, but indicators for young people show that the pressure to adapt skills remains high. Table 2 and Figure 1 summarise the main indicators. The youth (15-24) unemployment rate was 8.48% in 2021, fell to 7.72% in 2022 and 7.63% in 2023, and then turned upward to 7.83% in 2024, 8.64% in 2025 and 8.77% in 2026 (General Statistics Office of Vietnam [GSO], 2022, 2023a, 2023b, 2025; National Statistics Office of Vietnam [NSO], 2026a, 2026b). Over the same period, the unemployment rate of the working-age population declined from 3.22% in 2021 to 2.22% in both 2025 and 2026. As a result, the youth-to-working-age unemployment ratio rose steadily from 2.63 in 2021 to 3.89 in 2025 and 3.95 in 2026. In other words, a young person in the labour force is now almost four times as likely to be unemployed as an average working-age person, and this gap has widened in every period shown since 2021.

Table 2. *Selected youth labour market indicators in Vietnam, 2021-2026*

Period	Youth (15-24) UR (%)	Urban youth UR (%)	Working- age (%)	Youth-to- working- age ratio	Share with degrees/ certificates (%)	NEET youth (15-24)	Source
2021	8.48	11.91	3.22	2.63	26.1	n.r.	GSO (2022)
2022	7.72	9.70	2.32	3.33	26.2	n.r.	GSO (2023a)
2023	7.63	9.91	2.28	3.35	27.0	≈1.5 million (11.5%), Q4	GSO (2023b)
2024	7.83	9.35	2.24	3.50	28.3	≈1.3 million (10.0%), Q4	GSO (2025)
2025	8.64	11.23	2.22	3.89	29.2	≈1.4 million (10.2%), Q4	NSO (2026a)
2026	8.77	10.21	2.22	3.95	29.7	≈1.4 million (10.0%), Q2	NSO (2026b)

Note. UR = unemployment rate; NEET = not in employment, education or training; 2026 = first six months of 2026; n.r. = not reported in the release. Values are shown as first published in each release. Later releases revised some earlier estimates; for example, the 2025 release implies a revised 2024 youth unemployment rate of 7.92%. The youth-to-working-age ratio is the youth (15-24) unemployment rate divided by the working-age unemployment rate, calculated by the authors. Source: Compiled by the authors from GSO (2022, 2023a, 2023b, 2025) and NSO (2026a, 2026b).

Three points in Table 2 and Figure 1 deserve careful reading. First, the share of the labour force with formal training degrees or certificates increased from 26.1% in 2021 to 29.7% in 2026, yet youth unemployment has risen since 2024. This does not prove that the quality of training has declined, but it suggests that degrees and certificates alone do not guarantee a good match with a skill structure that is changing quickly. Second, about

one in ten young people (around 1.3-1.5 million persons) were not in employment, education or training (NEET) at recent reference points, which creates a risk that a group of young people will be left behind as firms move towards digital ways of working. Third, the pattern is shifting across areas: in 2025, urban youth unemployment reached 11.23%, 1.71 percentage points higher than in the previous year, whereas in 2026 the year-on-year increase came mainly from rural areas (7.96%, up 1.27 percentage points), while the urban rate (10.21%) was 0.43 percentage points lower than in 2025 (NSO, 2026a, 2026b). These movements cannot be attributed to AI, because cyclical conditions, the structure of labour demand and demographic factors also play a role. Nevertheless, in a context where firms are digitising and restructuring tasks, the data indicate a persistent skills-job matching problem in which AI competence is becoming an increasingly important element. For this reason, an AI skills strategy should be embedded in employment and youth development policy rather than left to voluntary technology courses.

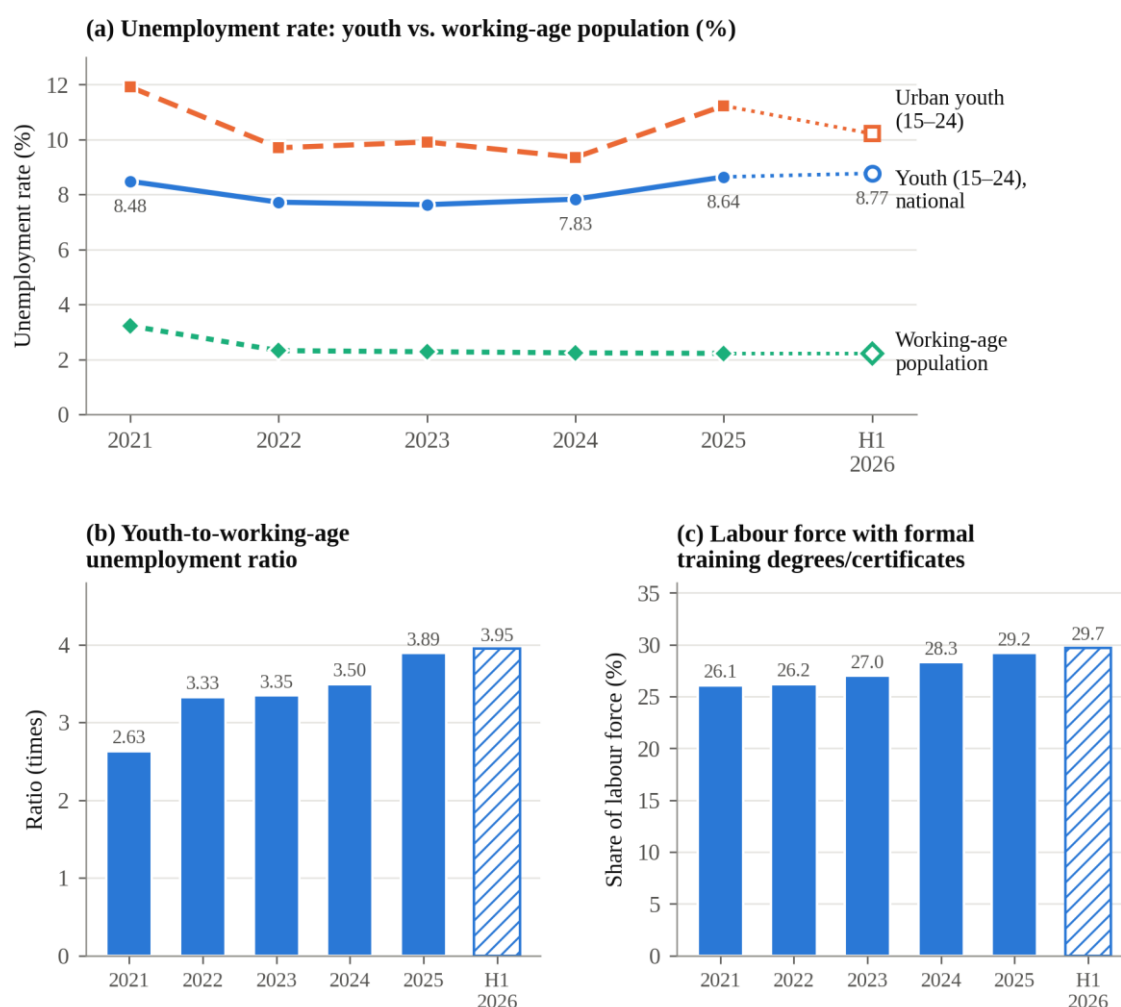


Figure 1. Youth unemployment and skill-transition pressure in Vietnam, 2021- 2026

Recent policy documents make this link explicit. Decision No. 1184/QĐ-TTg of 1 July 2026, which amends the Vietnam Youth Development Strategy 2021-2030, sets targets for 2030 that include providing basic digital skills to more than 80% of young people, aiming

for 40% of young people to have advanced digital skills and AI application skills, and reducing youth unemployment and underemployment to below 6% (PM, 2026a). The Law on Youth defines youth as citizens aged 16-30 (NA, 2020), whereas the statistical indicators above cover the 15-24 age group, so the two measures are not directly comparable. Still, the difference between the current youth unemployment rate of 8.77% and the 6% target shows the size of the challenge. At the national level, the new National Strategy on AI sets targets for 2030 to equip 10 million trained workers with basic AI skills, to train or retrain 500,000 workers to deploy and operate AI, and to raise labour productivity in AI-applying sectors by 10-15% (PM, 2026c). This is one of the few times that AI competence has been quantified directly in national targets. However, indicators such as “having AI application skills” or “equipped with basic AI skills” need to be operationalised through a common standard, assessment tools and evidence of results. If policy only counts the number of people trained, it may achieve an administrative output without necessarily improving productivity.

Note. Panel (a) compares the unemployment rate of youth aged 15-24 (national and urban) with that of the working-age population. Panel (b) shows the youth-to-working-age unemployment ratio calculated by the authors. Panel (c) shows the share of the labour force with formal training degrees or certificates. Values are as first published in each release; 2026 values are partial-year and not fully comparable with annual averages. Source: Authors’ compilation and calculations from GSO (2022, 2023a, 2023b, 2025) and NSO (2026a, 2026b).

4.2. Evidence on the mechanisms linking AI competence and work performance

The international evidence summarised in Table 3 allows three positive mechanisms to be identified. The first is *time saving and quality standardisation* in structured knowledge tasks, where productivity rises through both speed and output quality (Noy & Zhang, 2023). The second can be called *experience compression*: AI turns the good practices of experienced workers into real-time support for newcomers (Brynjolfsson et al., 2025). The third is the *expansion of knowledge coordination*: AI helps individuals access expertise that is normally spread across different functions (Dell’Acqua et al., 2026). For young workers, these three mechanisms are significant because they lower the cost of learning on the job, shorten the time needed to reach the expected standard and increase the ability to handle cross-functional tasks.

Table 3. Selected empirical evidence on AI, AI competence and work performance

Study	Design and sample	Main findings on performance	Implications for Vietnam
Noy and Zhang (2023)	Randomised experiment; 453 college-educated professionals	Task time fell by about 40% and output quality rose by about 18% for suitable writing tasks.	Measure time and quality together; do not use the number of AI uses as a performance indicator.

Study	Design and sample	Main findings on performance	Implications for Vietnam
Brynjolfsson et al. (2025)	Field data; 5,172 customer-support agents	Productivity rose by 15% on average; the largest gains were for less experienced and lower-skilled workers.	AI can support on-the-job learning and narrow skill gaps if it is built into workflows.
Dell’Acqua et al. (2023)	Field experiment; 758 consultants at Boston Consulting Group	Inside the frontier: 12.2% more tasks, 25.1% faster, over 40% higher quality. Outside the frontier: 19 percentage points less likely to be correct.	Train workers to recognise the limits of AI and set clear verification rules.
Dell’Acqua et al. (2026)	Pre-registered field experiment; more than 700 professionals at Procter & Gamble	Individuals with AI matched the quality of two-person teams without AI; AI reduced functional silos.	Design AI as a supporting “teammate”, not as a substitute for human accountability.
Tan et al. (2026)	Two-wave survey; 403 employee-supervisor dyads; moderated mediation model	Task-technology fit is the main mechanism linking AI literacy and performance; technostress weakens this path.	Measure task-technology fit and technostress in Vietnamese studies.
Naveed et al. (2026)	Survey of 300 academics in Pakistan; PLS-SEM, fsQCA and SHAP	AI literacy is positively associated with work performance ($\beta = 0.301$); work engagement mediates the link.	Use multi-method testing rather than relying only on linear regression.

Note. BCG = Boston Consulting Group; PLS-SEM = partial least squares structural equation modelling; fsQCA = fuzzy-set qualitative comparative analysis; SHAP = Shapley additive explanations. Source: Synthesised by the authors from the cited studies.

However, these benefits last only when users have matching competence. Within the “jagged frontier” framework, Dell’Acqua et al. (2023) show that users can be misled by AI when the task lies outside the area where the technology performs well. This is particularly risky for young workers, whose limited experience makes it harder to notice subtle errors and easier to confuse fluent language with professional correctness. Once users have passed the level of basic operation, verification skills may therefore have a higher marginal value than prompting skills. In the economics of skills, this is equivalent to saying that the

structure of returns to competence changes with the level of competence: at low levels, the ability to interact with AI raises output; at higher levels, judgement and risk control determine quality.

Studies that directly examine AI competence and performance increasingly support this relationship. Tan et al. (2026) show that collaborative AI literacy affects performance through task-technology fit, and that technostress changes the strength of this mechanism. Naveed et al. (2026), combining PLS-SEM, fsQCA and SHAP analysis on a sample of 300 academics, find a positive association between AI literacy and work performance, mediated by work engagement. These results should be interpreted with caution because most of them rely on survey data and non-Vietnamese samples. Nevertheless, they support the hypothesis that AI competence is not only a technical variable but also changes motivation, task structure and adaptive behaviour. This provides a reasonable basis for building a model to be tested specifically with young Vietnamese workers.

4.3. The institutional environment for AI, 2021-2026: from promoting applications to managing risks and building competence

Vietnam's AI policy framework can be divided into four phases. The first phase (2021-2022) focused on strategic direction. Decision No. 127/QD-TTg set objectives for AI research, development and application to 2030, and Decision No. 411/QD-TTg integrated AI into the development of the digital economy and digital society (PM, 2021, 2022). The emphasis at that time was on national capacity, infrastructure, the ecosystem and applications. The second phase (2024-2025) accelerated the institutionalisation of innovation. Resolution No. 57-NQ/TW raised science, technology, innovation and digital transformation to the level of a strategic breakthrough, while Resolution No. 193/2025/QH15 and Decree No. 88/2025/ND-CP created special pilot mechanisms (GoV, 2025; NA, 2025e; Politburo, 2024). The third phase (2025-2026) moved towards a dedicated, risk-based legal framework for AI and personal data. The fourth phase, which began in August 2026, focuses explicitly on AI human capital: the National Programme for AI Human Resource Development to 2030 sets a target of training or updating basic AI skills for at least 10 million workers, and its implementation schedule plans a national AI competency framework by June 2027 (PM, 2026b), while the new National Strategy on AI, which replaced Decision No. 127/QD-TTg, links AI adoption to productivity targets (PM, 2026c).

The Law on Artificial Intelligence No. 134/2025/QH15, which took effect on 1 March 2026, is a turning point because it establishes a human-centred approach to AI development and connects AI applications with responsibility, transparency, safety and human control (NA, 2025c). Decision No. 367/QD-TTg sets out the plan for implementing the Law, and Decree No. 142/2026/ND-CP, issued on 30 April 2026, details the classification of AI systems into high, medium and low risk levels, conformity assessment for high-risk systems, transparency, accountability, incident handling, controlled testing and ecosystem development (GoV, 2026; PM, 2026e). The Law on Personal Data Protection, in force since 1 January 2026, adds binding rules on how personal data may be processed (NA,

2025a). For workers' competence, the implication is clear: AI skills cannot be separated from compliance skills, data governance and human oversight. An employee who can produce outputs quickly but cannot classify sensitive data, does not know when a result must be checked or does not recognise transparency obligations cannot yet be regarded as competent in using AI at work.

Decree No. 142/2026/ND-CP also creates development tools that matter for the workforce, such as controlled testing, support for infrastructure and data, and support measures for small and medium-sized enterprises (SMEs) and start-ups (GoV, 2026). This opens the way from mass training to “learning by piloting”, in which firms test AI on specific processes under controlled conditions before scaling up (see Section 5.4). Such an approach is especially suitable for SMEs, for which the cost of a failed large-scale AI roll-out may be too high to absorb.

Decision No. 33/2026/QĐ-TTg, signed on 30 June 2026 and effective from 15 August 2026, issues a list of 46 high-risk AI systems in six fields: education, ethnic and religious affairs, health, banking, justice and transport (PM, 2026d). The fact that the list covers these fields shows that the required level of AI competence will differ by occupation. A young worker in banking or education needs not only to use tools but also to understand the obligations attached to decisions that may significantly affect individuals, organisations and their rights. This supports the argument that a national AI competence framework for workers should have a common core plus sector-specific modules, with the required proficiency increasing with the level of risk and the decision rights of each job position.

4.4. Current constraints and bottlenecks

First, Vietnam does not yet have a cross-sector standard of workplace AI competence with proficiency levels and a common assessment tool. The Digital Competence Framework for learners (MOET, 2025) and the national AI competency framework scheduled for 2027 (PM, 2026b) are important steps, but they still need to be translated into performance-based standards for people who are already working. Without such standards, the risk is “credentialism”: learners complete a course but cannot show that they can finish real tasks, verify outputs and handle risky situations. The same gap weakens research, because there are no comparable variables across sectors, regions and age groups.

Second, domain skills and AI skills may develop out of step. Young workers often learn to operate tools quickly but lack the sector knowledge needed to judge the quality of outputs. The more fluent generative AI becomes, the greater the risk of an “illusion of competence”: users feel that they complete more work but do not notice the error rate, the cost of corrections or the decline in quality. Training in writing prompts alone is therefore not enough; it must be combined with exercises in verification, testing, source tracing, error measurement and situations in which AI should not be used.

Third, many organisations have not yet redesigned their processes and KPIs for a human-AI model. When AI is simply added to an old process, employees must do their work as before and use AI on top of it, which increases cognitive load and technostress (Tan et al., 2026); when an organisation automates too quickly without human control

points, the risk of errors and legal liability rises. Performance therefore depends on the interaction between individual competence and organisational capability, a conditioning variable that future studies must measure.

Fourth, unequal access may turn into unequal productivity. Workers in large firms, urban areas and knowledge-intensive services usually have better access to paid tools, data, mentors and testing environments than workers in small firms, the informal sector or disadvantaged areas. Both Gmyrek et al. (2025) and the OECD (2023) emphasise that the effects of AI are linked to occupational structure and access to skills. Because a large share of employment in Vietnam is still informal, an AI policy that relies only on training in formal enterprises will miss a large part of the young workforce.

Fifth, causal evidence for Vietnam is still missing. Perception surveys may show that AI users rate themselves as more effective, but they cannot rule out self-report bias or selection bias: people with higher ability and motivation may both use AI more and perform better. A reliable research programme needs to combine validated competence scales, objective performance data and longitudinal, experimental or quasi-experimental designs. This is necessary to move from the general statement that “AI raises productivity” to precise estimates of *which* AI competence creates *how much* value, for *which* tasks and under *which* conditions.

5. Discussion and Policy Implications

5.1. Developing a workplace AI competence framework for young workers

The foundational solution is to develop a workplace AI competence module for young workers as part of, or aligned with, the national AI competency framework planned under Decision No. 1528/QĐ-TTg (PM, 2026b). The module should be usable on a voluntary basis by firms, education and training institutions and public employment services. It should not be a list of tool skills, because tools change quickly; instead, it should describe competence in terms of observable behaviour and results. The six proposed domains are summarised in Table 4, and each domain should have four proficiency levels: basic, operational, advanced, and leading or governance. The module can build on international measurement structures (Carolus et al., 2023; Long & Magerko, 2020; Wang et al., 2023) and on the Vietnamese validation results (Do et al., 2026), but it needs to move from “self-assessed knowledge” to “task-based performance assessment”.

Table 4. *Proposed domains of workplace AI competence and assessment indicators*

Competence domain	Evidence at the operational level	Suggested indicators	assessment
1. Understanding AI and its limits	Explains sources of bias, hallucination, data limits and situations where AI is unsuitable.	Scenario-based tests; rate of correctly identified errors and limits.	

Competence domain	Evidence at the operational level	Suggested indicators	assessment
2. Interaction design	Turns goals into requests with context, criteria, constraints and examples.	Quality of requests; number of iterations needed to reach an acceptable output.	
3. Workflow integration	Breaks down tasks; chooses which steps to automate, augment or keep under human decision.	Cycle time; share of standardised steps; cost per unit of output.	
4. Evaluation and verification	Checks sources, logic and figures; tests outputs before use.	Rate of undetected errors; accuracy; time spent on verification.	
5. Ethical, legal and data governance	Follows data classification, copyright, transparency and risk-management rules.	Data incidents; procedural violations; level of compliance with controls.	
6. Human-AI coordination and self-directed learning	Allocates roles, questions AI outputs, keeps accountability and updates skills.	Decision quality; ability to handle exceptions; speed of learning new skills.	

Note. Each domain is proposed to have four proficiency levels: basic, operational, advanced, and leading/governance. Source: Developed by the authors based on Carolus et al. (2023), Do et al. (2026), Long and Magerko (2020), MOET (2025) and Wang et al. (2023).

Regarding implementation, the agencies in charge of the national AI competency framework should work with the Ministry of Home Affairs (responsible for labour and employment), the Ministry of Science and Technology, the Ministry of Education and Training (responsible for higher education and vocational education), universities, business associations and technology firms. The standard should be open and reviewed every 12-18 months instead of being tied to the names of specific software products. Because Decision No. 1184/QĐ-TTg and the new National Strategy on AI already set quantified targets for AI skills (PM, 2026a, 2026c), a common standard is a necessary condition for turning these percentage and headcount targets into indicators that can be measured, compared and verified. In addition, since the Law on Artificial Intelligence and Decree No. 142/2026/ND-CP require AI development to go hand in hand with responsibility and risk control (GoV, 2026; NA, 2025c), compliance competence must be a compulsory part of the framework rather than an optional topic.

5.2. *Shifting AI training from “learning tools” to “learning by task, verification and responsibility”*

Training programmes should follow a four-step cycle: understand the task → collaborate with AI → verify → reflect and standardise. Each module should end with a professional product rather than a set of theoretical questions. For example, a marketing trainee should design a campaign, verify the data sources, assess brand consistency and keep a decision log; a finance trainee should use AI to support an analysis but check the figures, assumptions and sources; and an administrative trainee should identify which data must not be entered into public AI tools. This structure directly addresses the problem of the jagged frontier and discourages the attitude that “if AI can answer, the answer must be right”. Assessments should include situations in which AI gives a wrong but convincing answer, so that learners have to detect and correct the error.

Training should also be differentiated by role: general users focus on safety, requests and verification; domain specialists add process design and model evaluation; managers need to select use cases, measure returns, classify risks and design accountability; and technical staff need data, testing and quality-assurance skills. Because skill gaps remain a barrier to AI adoption (OECD, 2023) and the benefits of training spill over beyond individual firms, there is an economic case for public co-financing. For SMEs, support for access to AI infrastructure and services under Decree No. 142/2026/ND-CP can be combined with training vouchers to reduce initial costs (GoV, 2026).

5.3. *Redesigning jobs and building AI governance at the firm level*

Firms should avoid simply “buying accounts and letting staff use them as they wish”. A minimum operating model should include six layers: a list of approved use cases, data classification, risk classification, standards for permitted tools, human control points, and mechanisms for measuring results and incidents. For each process, the firm should map tasks into four groups: performed by humans; supported by AI; performed by AI but approved by humans; and automated under supervision. This design puts the automation-augmentation paradox into practice (Raisch & Krakowski, 2021) and is consistent with the principle, in Vietnam’s new AI legal framework, that human responsibility for decisions must not be replaced in sensitive situations (GoV, 2026; NA, 2025c).

KPIs for AI deployment should measure *net value* rather than *level of use*. Input indicators such as the number of accounts, the number of prompts or hours of training only reflect activity. Outcome KPIs should include task completion time, unit cost, error rate, quality scores, time spent on corrections, data incidents, the share of outputs that must be redone, the learning speed of new staff and the ability to maintain skills without AI. A project should be regarded as effective only if it improves at least one value outcome without significantly worsening risk indicators. This approach helps prevent “illusory productivity”, in which output increases but the costs of checking and correcting errors increase as well.

Responsible AI governance should also be seen as a productivity capability, not only as a compliance cost, because errors, rework, data loss, intellectual property disputes and

wrong decisions can cancel out productivity gains. The requirements of the Law on Artificial Intelligence and Decree No. 142/2026/ND-CP on risk management, transparency, accountability, conformity assessment and incident handling should therefore be translated into role-based operational checklists (GoV, 2026; NA, 2025c). For systems on the high-risk list, the requirements for control, documentation and staff competence must be higher (PM, 2026d). At the individual level, five minimum rules can be applied: (1) do not enter prohibited or sensitive data into unapproved tools; (2) verify important information; (3) disclose the use of AI whenever rules require it; (4) do not hand over final decisions that require human accountability; and (5) keep developing one's own professional skills. At the organisational level, firms need a risk owner, system logs, an incident reporting channel, periodic testing and risk-based impact assessments. Such rules create “operational trust” and allow firms to scale AI faster, because the boundaries of use are clear.

5.4. Using controlled testing and labour market information to build evidence

A new institutional advantage for Vietnam is the controlled testing mechanism within the AI legal framework. Decree No. 142/2026/ND-CP sets out principles and procedures for testing new systems within a defined scope, period and set of risk-management conditions (GoV, 2026). For productivity policy, this mechanism can be extended into “AI productivity labs”: select specific firms and processes; measure a baseline over 4-8 weeks; train the intervention group; compare it with a control group or a control period, for example with a difference-in-differences design; record quality, time, errors and incidents; assess whether skills are maintained; and only then scale up. The special mechanisms under Resolution No. 193/2025/QH15 and Decree No. 88/2025/ND-CP (GoV, 2025; NA, 2025e) can be used to fund such pilots on a results basis: co-financing firms that have a plan for training, testing and measurement; offering higher support rates for SMEs, manufacturing firms and disadvantaged areas; and requiring the publication of anonymised aggregate data for policy evaluation. In this way, public support for AI buys not only technology but also evidence of productivity and quality gains.

Vietnam also needs an AI skills information system that collects data from job postings, skill profiles, training programmes and enterprise surveys. Because AI usually changes the components of a job before it changes the job title, this skills map should be updated at the task level and should show which tasks are being transformed, which skills are complementary or declining, and which groups of workers face the largest transition risk. The Law on Employment, in force since 2026, provides a legal basis for connecting such a system with AI policy (NA, 2025d). For NEET youth, programmes should move from general support to short, modular skill pathways linked to job outcomes: an initial competence assessment, a foundation course in digital and AI skills, an occupation-specific module, a practical project with a firm and job matching. Policy should measure the employment rate and earnings 3-6 months after training, not only the number of people who complete a course. Given a youth unemployment rate of 8.77% and around 1.4 million

NEET youth in the second quarter of 2026 (NSO, 2026b), this outcome-based approach is urgent.

5.5. A proposed KPI framework for policies on young workers' AI competence

To prevent policy from stopping at slogans, we propose a three-tier KPI system. Tier one, *competence*, covers the share of young workers assessed against the standard, the median competence score, the share reaching the operational or advanced level, and gaps by gender, area, sector and firm size. Tier two, *adoption and results*, covers the share of AI-supported tasks with standardised processes, reductions in cycle time, improvements in quality, the share of new staff reaching the expected standard faster, and gains in earnings or job mobility. Tier three, *safety and sustainability*, covers the rate of serious errors, data incidents, outputs that must be redone, the share of tasks with human control points, the maintenance of domain skills and a technostress index. The KPIs should be measured before and after each intervention and, where possible, against a comparison group. Table 5 summarises the proposed indicators.

Table 5. Proposed three-tier KPI framework for policies on young workers' AI competence

Tier	KPI group	Core indicators	Data owner	Suggested frequency
Tier 1	Competence	Standardised AI competence score; share reaching the operational/advanced level; gaps between groups.	Training institutions, firms, employment services	Every 6-12 months
Tier 2	Adoption	Share of AI-supported processes that are standardised; share of positions with human-AI task descriptions.	Firms and public agencies	Quarterly
Tier 2	Performance	Cycle time; cost per output; quality; productivity; time for new staff to reach the standard.	Operational systems; HR performance data	Monthly or quarterly
Tier 2	Employment	Employment rate after training; earnings; job mobility; unemployment and NEET rates.	Employment and statistical agencies	Every 6-12 months
Tier 3	Risk	Error rate; data incidents; violations; share of outputs verified; AI incidents.	Risk management units	Monthly or quarterly

Tier	KPI group	Core indicators	Data owner	Suggested frequency
Tier 3	Sustainable capability	Ability to complete tasks without AI; domain skill scores; level of dependence; technostress.	Periodic assessment	Every 6-12 months

Note. The indicators are research and policy proposals, not current legal requirements. Baselines, targets and responsible actors should be defined for each sector. Source: Developed by the authors.

The indicators in Table 5 are research and policy proposals, not current legal requirements. When they are applied, each sector needs to define a baseline, targets, responsible actors and a measurement method. In particular, a target such as “100% of workers use AI” should be avoided, because some tasks are unsuitable for AI or carry high risk. A better target is “the share of workers who have sufficient competence to decide whether or not to use AI in an effective and responsible way”. This represents a shift from a policy of spreading tools to a policy of building competence.

6. Conclusion, Limitations and Future Research

This paper argues that workplace AI competence is a new form of human capital that can significantly affect the work performance of young workers, but that its effect is not automatic, not uniform and not linear. International evidence shows that generative AI can shorten task time, improve quality and raise productivity for suitable tasks, and that the benefits may be especially large for less experienced workers. At the same time, the evidence on the jagged technological frontier shows that AI can reduce quality when users do not recognise its limits or assign it the wrong tasks. Therefore, the decisive factor is not whether workers have access to AI, but whether they have the competence to allocate tasks, interact with AI, verify results, manage risks and coordinate effectively with AI.

In Vietnam, the period 2021-2026 shows two parallel movements. On the one hand, the youth labour market remains under skills-job matching pressure: the youth unemployment rate increased again from 2024 to 2026, and the youth-to-working-age unemployment ratio rose from 2.63 to 3.95, even though the share of workers with degrees or certificates kept rising (GSO, 2025; NSO, 2026a, 2026b). On the other hand, the institutional framework for AI developed very quickly, from the 2021 AI strategy to the Law on Artificial Intelligence and its implementing decree, the list of high-risk AI systems and, in August 2026, a new AI strategy and a national AI human resource programme (GoV, 2026; NA, 2025c; PM, 2026b, 2026c, 2026d). The gap between these two movements is the key policy space: institutions have moved fast, but the absorptive capacity of workers and organisations still needs to be measured, trained and governed accordingly.

The theoretical contribution of the study is a six-dimension structure of workplace AI competence and a conditional model in which task-technology fit, human-AI coordination

and organisational support act as important mediators and moderators. The policy contribution is a shift in focus from spreading AI use to building competence that can be demonstrated through results, from tool training to task-based training, from buying tools to redesigning jobs, and from measuring inputs to measuring net value and risk. This framework is consistent with the human-centred approach of Vietnam's new AI law and can be integrated into youth, employment, vocational education and enterprise support policies.

The study has five limitations. First, because it relies on secondary data, it cannot estimate the causal effect of AI competence on the work performance of young Vietnamese workers. Second, official statistics define youth as persons aged 15-24, whereas “young workers” in management research, and “youth” under the Law on Youth, may cover a wider age range; the indicators are therefore used as context and do not fully represent the population of future studies. Third, the international productivity evidence mainly concerns knowledge workers in highly digitised firms, so its applicability to the informal sector and labour-intensive industries in Vietnam needs to be tested. Fourth, the literature was selected through a structured but non-systematic procedure, so some relevant studies may have been missed. Fifth, AI technology changes quickly, and the skill structure and capability frontier may shift after the cut-off date of 28 September 2026.

Future research should carry out a multi-sector quantitative study of workers aged 18-30, or another clearly defined age range, using a six-dimension AI competence scale, a multidimensional performance scale and, where possible, objective performance data. The model could test the mediating roles of task-technology fit and human-AI coordination and the moderating roles of organisational support, task complexity and foundational skills. Methodologically, studies could combine PLS-SEM or covariance-based SEM with configurational methods such as fsQCA and, when conditions allow, conduct field experiments or difference-in-differences designs when firms roll out AI to different groups at different times. Such a research programme would provide sufficiently strong evidence to answer the most important question for Vietnam's productivity policy: how much value investment in the AI competence of young workers creates, for whom, in which types of tasks and under which governance arrangements.

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