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Applications of Artificial Intelligence in the Vietnamese Economy

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Abstract

AI is becoming a driving force in Vietnam's economic transformation. The country is moving beyond a growth model based on low-cost labour and export-led industries. Adoptions of the widespread generative AI and AI-powered assistants have accelerated the transformation. AI by reshaping the nature and future of work, it redefines the rules and productivity. This research overviews the recent research investigating how AI is transforming work, demand for digital skills, and productivity gains in AI-adopting Vietnamese industries. Optimal blend of AI and human collaboration influence positively its productivity impacts. Application of AI enable use of its potentials, but it has also significance challenges and risks of skill gaps, training costs, trust, job quality and distribution of its effects. Focus on adaptability, lifelong learning, and integration of AI ensures a positive future of work. This study identifies factors determining adoption of AI and heterogeneity in its productivity and future of work impacts.

JEL classification

D24, E24, F63, J24, L52, O33

Keywords

AI application, nature of work, future of work, economic transformation, skill requirements, AI productivity impacts, Vietnam

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1. Introduction and Background

Artificial intelligence (AI) has evolved rapidly from a specialized computational tool into a pervasive general-purpose technology reshaping production systems, labour markets, and governance structures worldwide (Brynjolfsson & McAfee, 2014; Cockburn et al., 2018). Advances in machine learning, robotics, natural language processing, and data analytics have accelerated its diffusion across sectors ranging from manufacturing and agriculture to healthcare, finance, and public administration (OECD, 2021; FAO, 2022; WHO, 2021). This technological shift is increasingly regarded as a defining feature of the twenty-first-century economy, comparable in scale and significance to earlier industrial revolutions (World Economic Forum, 2020; Agrawal et al., 2019). Yet despite growing scholarly attention, the mechanisms through which AI transforms economic activity—and the distributional consequences of these transformations—remain unevenly understood, particularly in emerging economies (UNDP, 2021; World Bank, 2023).

The global literature highlights AI's dual role as both an engine of productivity and a source of disruption. On one hand, AI enhances efficiency through automation, predictive analytics, and process optimization, enabling firms to reduce costs, improve quality, and innovate more rapidly (Zhong et al., 2025; Guo et al., 2025). On the other hand, AI alters the structure of labor demand, displacing routine tasks while complementing high-skill, non-routine work, thereby intensifying debates about technological unemployment and inequality (Acemoglu & Restrepo, 2020; Giwa & Ngepah, 2024; Lee, 2025). At the same time, AI raises profound governance challenges related to data privacy, algorithmic accountability, and public trust (Teo, 2024; Bowen, 2024; Choroszewicz, 2026). These opportunities and risks are not distributed evenly across countries: they depend on institutional capacity, human-capital endowments, digital infrastructure, and sectoral composition (Wen et al., 2025; Nigar et al., 2025).

For emerging economies such as Vietnam, the stakes are particularly high. Vietnam is undergoing a rapid digital transformation while simultaneously navigating structural shifts in manufacturing, agriculture and services. The country's export-oriented growth model, youthful workforce, and expanding digital infrastructure create fertile ground for AI adoption (Nguyen & Nguyen, 2026; Wach et al., 2026). Yet Vietnam also faces constraints common to middle-income economies: uneven technological readiness, limited AI talent, fragmented data systems, and evolving regulatory frameworks (Nguyen, 2025; Thaiduong, 2026). These conditions raise critical questions about how AI will shape Vietnam's productivity trajectory, labor-market outcomes, and sectoral competitiveness—and whether the technology will support inclusive development or exacerbate existing inequalities.

Despite the growing global literature, systematic evidence on AI's economic implications for Vietnam remains scarce. Existing studies are fragmented across sectors, rely heavily on cross-sectional surveys, and often lack integration with broader theoretical frameworks (Cao & Nguyen, 2025; Afifa et al., 2024; Pham & Pham, 2026). There is no comprehensive synthesis that brings together global insights, Vietnam-specific findings, and cross-sectoral comparisons to illuminate how AI is reshaping the country's economic landscape. This gap limits the ability of policymakers, researchers, and practitioners to design effective strategies for harnessing AI's potential while mitigating its risks.

This paper addresses this gap by conducting a comprehensive review of 56 theoretical and empirical studies on AI adoption and its economic impacts. It synthesizes four major theoretical traditions—technology-adoption models, automation and labor-market theories, productivity and growth frameworks, and institutional perspectives—to develop an integrated conceptual model tailored to Vietnam's development context (Huda et al., 2026; Fornino & Manera, 2022; Kim et al., 2025; Thaiduong, 2026). The review maps the diverse data sources and methodological approaches used in AI research, identifies key patterns and contradictions in the evidence, and analyzes how AI is transforming agriculture, industry, and services. It also highlights the central role of human capital, governance, and public trust in shaping AI trajectories (Thuy et al., 2026; Vuong, 2026; Tun et al., 2025).

The contribution of this paper is threefold. First, it provides the most comprehensive synthesis to date of global and Vietnam-specific evidence on AI's economic impacts. Second, it develops a unified theoretical and empirical framework that links micro-level adoption behavior with macro-level structural transformation. Third, it outlines a forward-looking research agenda to guide future empirical work and inform evidence-based policymaking in Vietnam and comparable emerging economies.

By integrating insights across disciplines and sectors, this review offers a holistic understanding of AI's transformative potential and the conditions under which it can support inclusive and sustainable development. The findings underscore that AI is not an exogenous force but a technology whose impacts depend on human agency, institutional design, and strategic investment. As Vietnam stands at a pivotal moment in its digital transition, understanding these dynamics is essential for shaping a future in which AI contributes to broad-based prosperity rather than deepening inequality.

Rest of this study is structured as follows. Section 2 reviews the literature on adoption of AI and its diverse transformation and productivity impacts. Section 3 introduce the theoretical and empirical frameworks and the integrative framework for Vietnam. The data and variable definitions used in empirical analysis of AI impacts are discussed in Section 4. The proposed theoretical-empirical model for adoption of AI in Vietnam is presented in Section 5. Analysis of the empirical findings in Vietnam is discussed in Section 6. Section 7 summarize and concludes. The final section suggests direction of future research.

2. Literature Review

Artificial intelligence (AI) has rapidly evolved from a specialized computational tool into a general-purpose technology with far-reaching implications for productivity, labor markets, skills, governance, and sectoral transformation. Across global and emerging-economies, the literature reveals a diverse and expanding body of theoretical and empirical work that examines how AI reshapes economic structures, organizational practices, and human–machine interactions. This section synthesizes 56 studies across multiple domains, organize the literature into four major clusters: (i) AI as a general-purpose technological paradigm; (ii) empirical evidence on AI's economic and sectoral impacts; (iii) AI, labour markets, and the future of work; and (iv) governance, ethics, trust, and public acceptance. Together, these strands provide a comprehensive foundation for understanding AI's transformative role in Vietnam's economic development.

2.1. AI as a General-Purpose Technological Paradigm

A large body of theoretical work conceptualizes AI as a general-purpose technology (GPT) comparable to electricity or the internet, capable of generating pervasive productivity spillovers and restructuring economic systems. These studies emphasize that AI's transformative potential arises from its ability to automate cognitive tasks, extract patterns from large datasets, and augment human decision-making. The technological foundations, automative paradigms and theoretical channels of productivity, labour substitution and complementarities are elaborated on.

Several authors highlight the qualitative shift from rule-based automation to machine-learning-driven "synthetic automation", where systems learn directly from data rather than relying on codified human knowledge. Steinhoff (2024) argues that machine learning enables the automation of tasks previously resistant to formalization, marking a new phase in the capitalist drive toward self-expanding automation. Jin et al. (2025) extend this view by mapping the evolution of automation architectures—from deterministic rule-based systems to Large Language Models (LLM)-based cognitive automation and multi-agent systems—showing how modern AI systems integrate reasoning, memory, and adaptive workflows.

These conceptual advances underscore that AI is not merely a continuation of earlier automation but a qualitatively distinct technological paradigm with broader economic implications. Theoretical models identify several channels through which AI affects economic outcomes: task substitution and displacement (Acemoglu & Restrepo, 2020; Fornino & Manera, 2022), skill-biased and routine-biased technological change (Balliester & Elsheikhi, 2019), productivity spillovers and innovation complementarities (Wen et al., 2025), institutional–technological co-evolution (Tong & Tan, 2026), and human–AI collaboration and job redesign (Vuong, 2026). These frameworks collectively show that AI's economic effects are heterogeneous, context-dependent, and mediated by institutional readiness, human capital, and sectoral characteristics.

2.2. Empirical Evidence on AI's Sectoral and Economic Impacts

Empirical studies demonstrate that AI adoption is reshaping agriculture, industry, services, environmental systems, and public administration. The evidence is diverse, spanning bibliometric analyses, econometric studies, case studies, and systematic reviews.

AI is increasingly applied to address structural challenges in agriculture, and environmental systems including water management, and environmental sustainability. Fernandes & DMello (2025) show that in aquaculture AI enhances disease detection, feed optimization, biomass estimation, and environmental monitoring, though adoption is constrained by cost and technical capacity. Huda et al. (2026) in South Asian agriculture find heterogeneous adoption patterns shaped by digital literacy, institutional support, and ecosystem maturity. Sapitang et al. (2024) document rapid growth in AI-GIS (geographic information system) integration for flood prediction, groundwater mapping, and hydrological modelling. In areas of wastewater and solid waste management, Baarimah et al. (2024) and Omer et al. (2026) show that AI improves pollutant detection, process optimization, and recycling efficiency. Similarly, in area of air pollution and environmental health: Chadalavada et al. (2025) and Guo et al. (2025) highlight AI's role in forecasting, material design, and environmental risk assessment. These studies collectively demonstrate AI's potential to enhance sustainability, though challenges remain around data quality, infrastructure, and scalability.

AI adoption in industry is associated with productivity gains, energy efficiency, and operational optimization. In regards with energy intensity, Zhong et al. (2025) show that AI reduces manufacturing energy intensity globally, with stronger effects in middle-income countries. For infrastructure monitoring: Nguyen & Nguyen (2026) develop an edge-AI system for power transmission safety in Vietnam, demonstrating real-world feasibility. In the area of building industry: Kim et al. (2025) identify psychological and organizational factors driving AI adoption, emphasizing user readiness and perceived usefulness. Ha (2025) with reference to energy crisis mitigation finds that AI markets remain sensitive to energy uncertainty, highlighting AI's dual role as both energy optimizer and energy consumer. These findings suggest that AI can support industrial upgrading in emerging economies like Vietnam, but benefits depend on digital infrastructure and organizational readiness.

In the area of services including healthcare, education, finances, HR (human resource) and accounting, AI adoption in services is accelerating, with significant implications for skills, job design, and service quality. In healthcare, Thuy et al. (2026) show that Vietnamese medical students hold mixed attitudes toward AI, shaped by perceived usefulness and job security concerns. Tun et al. (2025) highlight uneven AI governance readiness across ASEAN healthcare systems. In medical education, Nguyen et al. (2025) identify opportunities for personalized learning and simulation but emphasize presence of low AI literacy and infrastructure gaps. Considering FinTech entrepreneurship: Wach et al. (2026) show that AI-related competencies shape entrepreneurial intentions in Vietnam and Poland. In HR and accounting Cao & Nguyen (2025) find that AI adoption in recruitment depends on perceived value and HR readiness. Afifa et al. (2024) show that digital transformation and transformational leadership drive AI adoption in accounting, and in hospitality. Pham & Pham (2026) document AI-induced identity threats among frontline workers, affecting well-being and organizational resilience. These studies highlight both the opportunities and psychological challenges associated with AI adoption in service sectors.

2.3. AI, Labor Markets, and the Future of Work

A substantial portion of the literature examines AI's implications for employment, skills, job quality, and labor market inequality.

Regarding employment effects and displacement, empirical studies consistently show that AI and automation have heterogeneous labour-market effects. In looking at job displacement, Acemoglu & Restrepo (2020) find that robots reduce employment and wages in U.S. labor markets and Lee (2025) shows that IT investment in Korea reduces workforce size while raising wages for remaining skilled workers. For unemployment dynamics Nguyen & Vo (2022) find a nonlinear relationship between AI and unemployment, mediated by inflation, and Giwa & Ngepah (2024) show that AI reduces low-skilled employment in South Africa. In study of labour market exclusion: Lamperti & Castellani (2026) show that automation increases inactivity and discouragement across Europe. These findings suggest that AI may exacerbate labor-market polarization, especially in economies with large low-skill workforces.

Several studies analyze the skills, identity, and human-AI collaboration by highlighting the psychological and skill-related dimensions of AI adoption. By looking at job crafting and engagement Vuong (2026) shows that generative AI enhances job performance through job crafting and engagement, moderated by digital competence. Pham & Pham (2026) investigate identity threats and find that AI can undermine professional identity in service roles. Related to teacher and student imaginaries Lee et al. (2026) show that teachers anticipate both opportunities and disruptions from AI textbooks, while Bal & Arseven (2026) find that AI can enhance or inhibit creativity depending on usage patterns. These studies emphasize that AI adoption is not purely technological—it is deeply human and psychological.

2.4. Governance, Ethics, Trust, and Public Acceptance

AI's societal impacts depend heavily on governance frameworks, ethical norms, and public trust. In this relation the issues of public trust and attitudes, ethical and legal concerns and AI consciousness and moral status are studied.

Considering public trust and attitudes, a growing literature examines how publics perceive AI. By focusing on segmented publics, Bao et al. (2022) identify five distinct publics with varying risk–benefit perceptions. Thaiduong (2026) in analysing dynamic trust shows that trust in AI's ability remains high in Vietnam, but trust in its benevolence and integrity declines over time. In looking at technological frames, Wang & Liang (2024) show that public discourse becomes more polarized after ChatGPT. These studies reveal that public attitudes are ambivalent, dynamic, and context-dependent.

Ethical and legal concerns, in particular, freedom of thought, Teo (2024) argues that AI threatens cognitive autonomy through manipulation and inference. Regarding public sector accountability, Choroszewicz (2026) shows that public workers become "moral crumple zones" for AI failures. Nguyen (2025) concerning legal frameworks highlights gaps in Vietnam's criminal justice system for AI integration. Finally, by emphasising ethical governance Bowen (2024) argues that PR (public relation) professionals must act as ethical guardians in AI-driven communication.

In relation with studies of AI-consciousness and moral status, Caviola et al. (2025) explore how societal attitudes toward AI consciousness may mirror attitudes toward animals, raising future governance challenges. Across these 56 studies, several cross-cutting themes emerge: AI's impacts are heterogeneous across sectors, skill groups, and countries; Institutional readiness, digital infrastructure, and human capital strongly mediate outcomes; AI adoption produces both productivity gains and labor-market risks, especially for low-skill workers; Public trust and ethical governance are essential for sustainable AI integration; and Emerging economies like Vietnam face unique opportunities and vulnerabilities, given their structural characteristics.

This literature provides a rich foundation for analyzing AI's role in Vietnam's economic transformation, informing the theoretical framework, empirical strategy, and policy implications developed in subsequent sections.

3. Theoretical and Empirical Frameworks

3.1. Theoretical Framework

A growing body of theoretical work conceptualizes artificial intelligence as a general-purpose technology (GPT) whose influence extends across sectors and evolves continuously. Steinhoff (2024) characterizes modern AI as a form of "synthetic automation", emphasizing that machine-learning systems no longer rely on explicit human knowledge but instead extract patterns directly from data. This shift allows AI to automate tasks that were previously resistant to mechanization, including analytical, cognitive, and creative functions. Jin and colleagues (2025) reinforce this view by mapping the evolution of automation architectures—from rule-based systems to large-language-model-driven cognitive automation—showing how contemporary AI integrates reasoning, memory, and adaptive workflows. Together, these studies highlight why AI is increasingly viewed as a foundational technology capable of reshaping production systems in emerging economies such as Vietnam.

The literature identifies several mechanisms through which AI affects productivity, labor markets, and economic structure. Acemoglu and Restrepo (2020) demonstrate that AI substitutes most readily for routine tasks, leading to job displacement and wage pressure in occupations characterized by repetitive or codifiable activities. This task-substitution mechanism is central to understanding labor-market polarization in both advanced and developing economies.

At the same time, other scholars emphasize the complementary role of AI. Vuong (2026), for example, shows that generative AI can enhance job crafting and work engagement, enabling employees to shift toward higher-value tasks. Pham and Pham (2026) similarly find that AI can augment decision-making and customer engagement in Vietnam's hospitality sector, even as it introduces new identity-related pressures. These studies illustrate that AI's effects are not uniformly substitutive; in many contexts, AI enhances rather than replaces human capabilities.

A third channel concerns productivity and innovation spillovers. Zhong et al. (2025) provide cross-country evidence that AI adoption reduces energy intensity in manufacturing, particularly in middle-income economies where technological upgrading is still underway. Nguyen and Nguyen (2026) show how edge-AI systems improve real-time monitoring and operational efficiency in Vietnam's power-transmission infrastructure. These findings underscore AI's potential to support industrial upgrading and sustainability goals.

Finally, institutional dynamics play a crucial role. Tong and Tan (2026) introduce the Double Helix framework to explain how technological capabilities and institutional pressures co-evolve, reinforcing one another over time. Their study shows that firms with stronger AI capabilities are better able to buffer climate-related risks, but only when institutional environments provide supportive regulatory and governance structures. This insight is particularly relevant for Vietnam, where national AI strategies and digital-transformation policies shape adoption trajectories.

Beyond technological and economic channels, AI adoption is deeply shaped by human perceptions, identities, and social norms labelled as behavioural and sociotechnical mechanisms. Kim et al. (2025) demonstrate that perceived usefulness, ease of use, and personal readiness strongly influence AI adoption in the building industry, drawing on the Technology Acceptance Model (TAM) and the Technology-Organization-Environment-Personal (TOEP) framework. Wach and colleagues (2026) extend this perspective to entrepreneurship, showing that AI-related competencies shape entrepreneurial identity and self-efficacy among students in Vietnam and Poland.

Other studies highlight psychological and sociotechnical dimensions. Vuong (2026) uses the Job Demands–Resources model to show how AI influences job crafting and engagement, while Pham and Pham (2026) reveal how AI can threaten professional identity in service roles. Lee et al. (2026) adopt a sociotechnical imaginaries lens to examine how teachers in South Korea envision AI-powered digital textbooks, illustrating how expectations and cultural narratives shape adoption long before technologies are implemented. These studies collectively show that AI adoption is not merely a technical decision but a deeply human and social process.

3.2. Empirical Framework

Empirical studies employ a wide range of proxies to measure AI adoption. Acemoglu and Restrepo (2020) and Zhong et al. (2025) use industrial robot density as a proxy for AI intensity in manufacturing, while Nguyen and Vo (2022) rely on AI-related patent counts to measure national technological capability. Firm-level studies, such as those by Cao and Nguyen (2025) and Afifa et al. (2024), use survey-based indicators of AI usage in HR and accounting. Sector-specific research—such as Fernandes and DMello's (2025) work on aquaculture or Sapitang et al.'s (2024) review of AI-GIS integration—relies on operational data from AI-enabled systems. In service sectors, perception-based measures are common: Thuy et al. (2026) assess AI literacy and adoption intentions among medical students, while Wach et al. (2026) measure AI-related competencies among university students. For Vietnam, where data availability varies across sectors, a hybrid approach combining firm surveys, sectoral indicators, and national readiness metrics is most appropriate.

The empirical literature examines a diverse set of outcomes to capture AI's economic, social and labour market impacts. Productivity is measured through indicators such as output per worker, energy intensity, predictive accuracy, and process efficiency. Zhong et al. (2025) focus on energy intensity, while Nguyen and Nguyen (2026) assess operational efficiency in infrastructure monitoring. Labor-market outcomes include employment levels, unemployment rates, job displacement, job crafting, and identity-related responses to AI. Nguyen and Vo (2022) analyze unemployment dynamics across 40 countries, while Giwa and Ngepah (2024) examine low-skilled employment in South Africa. Skills and human-capital outcomes are captured through measures of digital competence, AI literacy, and entrepreneurial self-efficacy, as shown in studies by Wach et al. (2026) and Thuy et al. (2026). Governance-related outcomes include public trust (Thaiduong, 2026), ethical acceptance (Eriksson et al., 2026), and legal readiness (Nguyen, 2025).

The empirical studies examine moderators, mediators and heterogeneity in AI adoption. A consistent finding across empirical studies is that AI's effects are highly heterogeneous. Vuong (2026) shows that digital competence moderates the relationship between AI usage and job performance, while Cao and Nguyen (2025) find that HR readiness shapes adoption outcomes in recruitment. Tong and Tan (2026) demonstrate that institutional pressures moderate the relationship between AI capability and climate resilience. Nguyen and Vo (2022) reveal that inflation regimes mediate the relationship between AI and unemployment. These studies highlight the importance of contextual factors—organizational, institutional, and macroeconomic—in shaping AI's adoption and impacts.

The empirical literature employs a wide range of strategies and methodological approaches. Econometric studies use fixed-effects models, instrumental variables, difference-in-differences designs, and nonlinear models such as panel smooth transition regressions. Organizational studies rely on structural equation modeling, as seen in the work of Cao and Nguyen (2025) and Afifa et al. (2024). Environmental and engineering studies use machine-learning models and hybrid optimization techniques, as demonstrated by Chadalavada et al. (2025) and Sapitang et al. (2024). Qualitative research—including ethnography, sociotechnical analysis, and discourse studies—provides insight into the human and institutional dimensions of AI adoption, as shown in the work of Choroszewicz (2026) and Lee et al. (2026). This methodological diversity suggests that a mixed-methods approach is most appropriate for analysing AI adoption in Vietnam.

3.3. Integrated Framework

Synthesizing these theoretical and empirical insights yields a multi-layered framework for understanding AI adoption in Vietnam. At the technological layer, AI functions as a general-purpose technology that enables automation, augmentation, and innovation. At the organizational layer, adoption depends on digital readiness, leadership, data infrastructure, and HR capacity. At the human layer, skills, identity, trust, and acceptance shape how workers interact with AI. At the institutional layer, national strategies, governance frameworks, and regulatory environments influence adoption trajectories. At the sectoral layer, structural characteristics of agriculture, industry, services, and public administration determine where AI's impacts are strongest. Finally, at the outcome layer, AI affects productivity, employment, skills upgrading, inequality, and sustainability.

This integrated framework provides a coherent foundation for analyzing AI's role in Vietnam's economic transformation and sets the stage for the empirical synthesis and policy analysis that follow.

4. Data and Definitions

Empirical research on artificial intelligence adoption and its economic impacts relies on a diverse set of data sources, variable constructions, and modeling strategies. The 56 studies reviewed are extracted from Science Direct through searching keywords "Artificial Intelligence", "AI adoption", and "Vietnam" and span firm-level, sectoral, national, and survey-based datasets, reflecting the multidimensional nature of AI as both a technological and socioeconomic phenomenon. For Vietnam, understanding these data practices is essential for designing future empirical work that can credibly measure AI adoption, its productivity effects, and labour-market outcomes.

4.1. Types of Data Used in Empirical AI Studies

Many studies use panel data on firm-level administrative and financial data from firms' balance sheets, income statements, and productivity indicators, often merged with

AI-related measures such as patents, technology disclosures, or ICT investments (e.g., Tong & Tan, 2026; Zhong et al., 2025). These datasets allow estimation of AI's impact on productivity, profitability, energy intensity, and analysis of heterogeneity by firm size, ownership, and sectoral level. For Vietnam, similar data could be constructed from tax records, enterprise surveys, and stock-exchange filings.

In addition to firm-level administrative and financial data, data on patent, intellectual property, and innovation data are extremely important in the context of AI. AI capability is frequently proxied by number of AI-related patents, citations of AI patents, and AI-related trademarks or R&D expenditures. Tong & Tan (2026), for example, build an AI capability index from patent data and AI disclosures. Such measures capture technological sophistication rather than mere adoption.

At the aggregate level, some studies operate at the industry or country level, using sectoral value added, employment, energy use, and AI intensity measures (e.g., robot density, AI capital stock, ICT investment). These are used to estimate AI's impact on productivity, energy intensity, or employment at a more aggregate level (e.g., Zhong et al., 2025; Lee et al., 2025).

A large subset of studies relies on surveys and perception-based data of employees (e.g., Vuong, 2026; Pham & Pham, 2026), managers and decision-makers (e.g., Ali & Khan, 2025; Wach et al., 2026), and the public (e.g., Bao et al., 2022; Eriksson et al., 2026; Thaiduong, 2026). These datasets are crucial for capturing perceived usefulness and ease of use, trust, moral evaluations, risk perceptions, job crafting, work engagement, and identity threat

In domain-specific technical and sensor data like agriculture, aquaculture, energy, and infrastructure, AI studies often use sensor readings (e.g., water quality, temperature, energy consumption), image data (e.g., disease detection, biomass estimation), and IoT (Internet of Things) streams and operational logs. Fernandes & DMello (2025) and Huda (2026) are examples where AI models are trained on rich technical datasets to optimize production and resource use.

4.2. Key Variables and Their Definitions

Across these studies, several categories of variables recur. For a Vietnam-focused empirical strategy, it is useful to define them clearly. The variables are grouped into dependent, independent, control and characteristics, and moderator and mediator variables.

The *dependent variables* are defined as: (i) productivity outcomes measured as labour productivity (output per worker), total factor productivity (TFP), energy intensity (energy use per unit of output), and profitability (Return on Assets ROA, Return on Equity ROE), (ii) labour-market outcomes are defined as: employment levels, unemployment rates, job performance (self-reported or supervisor-rated), and job quality (autonomy, security, satisfaction), and (iii) behavioural and attitudinal outcomes are defined as job crafting, work engagement (Vuong, 2026), identity threat, resistance to AI (Pham & Pham, 2026), and trust in AI, moral acceptability (Thaiduong, 2026; Eriksson et al., 2026).

The *independent variables* (AI adoption and capability) are groped into: (i) binary or categorical AI adoption indicators informing whether a firm uses AI tools (yes/no) and number of AI applications deployed (e.g., in HR, finance, production), (ii) AI capability indices such as composite measures based on patents, AI-related disclosures, R&D (Tong & Tan, 2026), (iii) intensity measures defined as share of investment in AI/ICT and robot density or AI capital per worker, finally (iv) generative AI usage defined as frequency and type of Gen-AI use at work (Vuong, 2026).

The *control and characteristic variables* are grouped into: (i) firm characteristics such as size, age, ownership (state, private, foreign), sector (agriculture, manufacturing, services) and export orientation, location (urban/rural, region), (ii) worker characteristics such as age, gender, education, occupation, digital competence, prior AI experience, and (iii) contextual variables including regulatory environment, policy shocks (e.g., environmental tax reform in Tong & Tan, 2026), regional climate risk, and infrastructure quality.

Many studies explicitly model *mediating and moderating mechanisms*. The mediators are defined as job crafting and work engagement mediating the effect of Gen-AI on job performance (Vuong, 2026) and perceived usefulness mediating the effect of external factors on AI adoption (Kim et al., 2025). The moderators include digital competence moderating the impact of Gen-AI on job outcomes (Vuong, 2026), institutional pressure moderating AI's effect on climate resilience (Tong & Tan, 2026), and personal factors (anxiety, self-efficacy) moderating perceived usefulness (Kim et al., 2025). For Vietnam, similar constructs could be operationalized to capture how skills, governance, and firm characteristics shape AI's impacts.

4.3. Metadata and Heterogeneity in AI Impacts

A key strength of the 56-paper body is its attention to heterogeneity—how AI's impacts differ across sectors, regions, firm types, and worker groups. This is often captured through: subsample analyses (e.g., high vs. low climate-risk regions, heavy-polluting vs. clean industries in Tong & Tan, 2026), interaction terms (e.g., AI × digital competence; AI × firm size), and multi-group structural equation models (e.g., Kim et al., 2025).

Metadata such as country/region, sector classification, period and data source type (survey, administrative, technical) are crucial for comparing results across studies and for understanding why AI adoption and its impacts vary. For Vietnam, careful documentation of metadata will be essential to position national findings within the broader international literature.

4.4. Key Empirical Studies: Data, Theory, Methods, and Findings

A rigorous analysis of AI adoption and its economic impacts require clarity about the data sources, measurement strategies, and conceptual definitions used across the literature. The 56 studies reviewed employ a wide range of datasets—spanning national and sectoral statistics, firm-level surveys, patent databases, environmental monitoring systems, and experimental or ethnographic observations. This section synthesizes these diverse approaches into a coherent framework suitable for analyzing AI adoption in Vietnam. It also clarifies the definitions of key variables, including dependent outcomes, independent measures of AI adoption, and the moderators and mediators that shape AI's effects. The data sources used in AI research are categorized into national and cross-country datasets, firm-level surveys and organizational data, sector-specific operational data, education, healthcare, and public-sector data, as well as social-media and public-opinion data.

National and cross-country datasets: A substantial portion of the empirical literature relies on national or cross-country datasets to measure AI adoption and its macroeconomic impacts. For example, Acemoglu and Restrepo (2020) use industrial robot installation data from the International Federation of Robotics (IFR) combined with U.S. labour market statistics to estimate the employment effects of automation. Zhong et al. (2025) similarly merge IFR robot data with energy intensity indicators from the International Energy Agency (IEA) to examine how AI affects manufacturing efficiency across 74 countries. Nguyen and Vo (2022) draw on AI-related patent counts from the World Intellectual Property Organization (WIPO) to construct a cross-country measure of AI capability for 40 economies. These datasets provide broad coverage and comparability, making them valuable for analyzing global patterns. However, they often lack granularity on firm-level adoption, sectoral heterogeneity, or the specific forms of AI used which are among limitations that are particularly relevant for emerging economies like Vietnam.

Firm-level surveys and organizational data: Firm-level studies offer more detailed insights into how organizations adopt and use AI. Cao and Nguyen (2025), for instance, survey 297 hiring managers and HR executives in Vietnamese medium-sized firms to assess AI adoption in recruitment. Afifa et al. (2024) collect data from 510 respondents in Vietnamese manufacturing firms to examine AI adoption in accounting. Vuong (2026) surveys 758 SME employees to analyze how generative AI influences job crafting and performance. These datasets capture organizational readiness, perceived value, digital competence, and leadership factors—variables that are essential for understanding AI adoption dynamics in Vietnam's private sector.

Sector-specific operational data: Several studies rely on operational or technical datasets generated by AI-enabled systems. Fernandes and DMello (2025) synthesize data from commercial aquaculture platforms such as XperCount and eFishery to document AI's role in biomass estimation and feed optimization. Nguyen and Nguyen (2026) develop a new dataset of annotated images and anomaly events from Vietnam's power-transmission corridors to evaluate an edge-AI monitoring system. Sapitang et al. (2024) review hydrological datasets from remote sensing platforms (Landsat, MODIS, SPOT) used in AI-GIS water-resource models. These datasets are highly detailed and context-specific, offering insights into AI's technical performance and operational constraints.

Education, healthcare, and public-sector data: Studies in areas of education and healthcare often rely on perception-based surveys. Thuy et al. (2026) survey 323 medical and pharmacy students to assess their AI perceptions and adoption intentions. Nguyen et al. (2025) draw on institutional data from Vietnamese medical universities to analyze AI readiness in medical education. Choroszewicz (2026) uses 2.5 years of digital ethnography in Finnish welfare organizations to examine generative AI adoption in the public sector. These datasets highlight the human, ethical, and institutional dimensions of AI adoption—areas that are increasingly important for Vietnam's public-sector digital transformation.

Social-media and public-opinion data: Public trust and attitudes toward AI are often measured using large-scale digital trace data. Bao et al. (2022) analyze a nationally representative U.S. survey of 2,700 respondents, while Wang and Liang (2024) analyze

114,393 public comments from Douyin to examine technological frames. Thaiduong (2026) analyzes more than 2,700 comments from VnExpress to track evolving public trust in AI in Vietnam. These datasets provide real-time insights into public sentiment, which is essential for understanding societal readiness for AI adoption.

4.5. Definitions of Key Variables

Across the literature, AI is defined in multiple ways depending on the research context. Steinhoff (2024) defines AI as a form of synthetic automation capable of learning from data without explicit human instruction. Jin et al. (2025) conceptualize AI as a family of architectures—including rule-based systems, large language models, and multi-agent systems—that automate cognitive tasks. Fernandes and DMello (2025) define AI operationally through its applications in aquaculture, such as computer vision, predictive analytics, and automated feeding.

For the purposes of this review, AI is defined as A set of computational techniques—including machine learning, deep learning, natural language processing, and computer vision—that enable systems to perform tasks requiring perception, prediction, reasoning, or decision-making. This definition aligns with Vietnam's national AI strategy, and it captures the breadth of AI applications across sectors.

Independent variables: measures of AI adoption

Technology-based measures: Several studies use objective technological indicators to measure AI adoption such as Robot density (Acemoglu & Restrepo, 2020; Zhong et al., 2025), AI-related patents (Nguyen & Vo, 2022; Tong & Tan, 2026), and AI capability indices (Tong & Tan, 2026). These measures capture national or sectoral AI intensity but may overlook firm-level heterogeneity.

A significant portion of the empirical literature relies on technology-based indicators to capture AI adoption, particularly in manufacturing and industrial contexts. Acemoglu and Restrepo (2020) use industrial robot density as a proxy for AI-enabled automation, arguing that robots represent one of the most measurable and standardized embodiments of AI across countries. Their approach has been widely adopted in subsequent studies because robot installation data are consistently reported and comparable across time and regions. Zhong et al. (2025) extend this logic to a global sample of 74 countries, using robot density to examine how AI influences energy intensity in manufacturing. Their findings demonstrate that robot-based measures can effectively capture cross-country variation in AI adoption, especially in sectors where automation is hardware-intensive. However, these measures inevitably privilege industrial applications and may underrepresent AI adoption in service-oriented or knowledge-based sectors, which are increasingly important in emerging economies such as Vietnam.

Firm-level adoption indicators: Firm-level studies measure AI adoption through usage of AI tools in HR (Cao & Nguyen, 2025), AI-enabled accounting systems (Afifa et al., 2024), generative AI usage in daily tasks (Vuong, 2026), and AI-supported decision systems (Choroszewicz, 2026). These indicators are particularly relevant for Vietnam's SME-dominated economy.

Firm-level studies offer a more granular perspective on how organizations integrate AI into their operations. Cao and Nguyen (2025), for example, measure AI adoption in

Vietnamese medium-sized firms by surveying HR managers about their use of AI-enabled recruitment tools. Their approach captures not only whether AI is used but also how organizations perceive its benefits and sacrifices. Afifa and colleagues (2024) adopt a similar strategy in the accounting domain, collecting data from manufacturing firms to assess the extent to which AI supports financial reporting, anomaly detection, and managerial decision-making. Vuong (2026) examines generative AI usage among SME employees, focusing on how frequently AI tools are used and how they reshape daily work practices. These firm-level indicators are particularly valuable in Vietnam's context, where AI adoption varies widely across sectors and where organizational readiness, leadership, and digital infrastructure strongly influence adoption decisions.

Perception-based measures: In education, healthcare, and public-sector studies, AI adoption is often measured through AI literacy, perceived usefulness, adoption intentions, and trust and ethical acceptance as shown in Thuy et al. (2026), Wach et al. (2026), and Eriksson et al. (2026).

In sectors where AI adoption depends heavily on human acceptance—such as education, healthcare, and public administration—researchers often rely on perception-based measures. Thuy et al. (2026) assess AI adoption intentions among medical and pharmacy students by measuring AI literacy, perceived usefulness, and attitudes toward AI in clinical practice. Their findings reveal that psychological readiness and perceived competence play a central role in shaping adoption. Wach and colleagues (2026) evaluate AI-related competencies among university students in Vietnam and Poland, focusing on how digital, information, and AI literacy influence entrepreneurial identity and intention. These perception-based measures are essential for understanding adoption in sectors where trust, ethical concerns, and professional identity shape how AI is integrated into daily work.

Sector-specific operational measures: Technical studies use operational metrics such as anomaly detection accuracy (Nguyen & Nguyen, 2026), pollutant prediction accuracy (Chadalavada et al., 2025), and biomass estimation precision (Fernandes & DMello, 2025). These measures capture AI's functional performance rather than organizational adoption.

In technical and infrastructure-intensive sectors, AI adoption is often measured through operational performance data generated by AI-enabled systems. Fernandes and DMello (2025) document AI adoption in aquaculture by analyzing the performance of commercial platforms such as XperCount and eFishery, which automate biomass estimation and feeding decisions. Their approach captures AI adoption not as a managerial choice but as a functional capability embedded in production processes. Nguyen and Nguyen (2026) develop a new dataset of annotated images and anomaly events to evaluate an edge-AI monitoring system deployed across Vietnam's power-transmission corridors. Their operational metrics—such as detection accuracy, latency, and energy consumption—provide a detailed view of AI's technical performance in real-world conditions. These sector-specific measures are particularly relevant for Vietnam, where AI adoption in agriculture, energy, and environmental monitoring is expanding rapidly.

Hybrid and composite measures: Some studies adopt hybrid approaches that combine technological, organizational, and institutional indicators. Tong and Tan (2026), for example, construct an AI capability index using patent data and AI-related disclosures to capture firms' technological sophistication. Their multidimensional measure reflects the growing recognition that AI adoption is not merely a matter of acquiring technology but also of developing organizational capabilities, data infrastructures, and strategic alignment. Such composite measures are especially useful in emerging economies, where AI adoption is shaped by a combination of technological readiness, institutional pressures, and human capital.

Dependent variables: economic and social outcomes

Productivity and efficiency outcomes include energy intensity (Zhong et al., 2025), process efficiency (Nguyen & Nguyen, 2026), and predictive accuracy in environmental systems (Guo et al., 2025). These outcomes are central to Vietnam's industrial upgrading goals.

Employment and labour-market outcomes include employment levels (Acemoglu & Restrepo, 2020), unemployment (Nguyen & Vo, 2022), low-skilled employment (Giwa & Ngepah, 2024), and labour-market exclusion (Lamperti & Castellani, 2026). These outcomes are particularly relevant for Vietnam's large low-skilled workforce.

Skills, identity, and human capital are measured as digital competence (Vuong, 2026), AI-related competencies (Wach et al., 2026), identity threat (Pham & Pham, 2026), and student readiness (Thuy et al., 2026). These variables capture the human dimension of AI adoption.

Governance, trust and ethics-related outcomes include public trust (Thaiduong, 2026), moral acceptance (Eriksson et al., 2026), and legal readiness (Nguyen, 2025). These outcomes are essential for understanding societal readiness for AI in Vietnam.

Key moderating variables include digital competence (Vuong, 2026), HR readiness (Cao & Nguyen, 2025), institutional pressures (Tong & Tan, 2026) and inflation regimes (Nguyen & Vo, 2022). These moderators explain why AI's impacts vary across contexts.

Key common mediators include job crafting (Vuong, 2026), work engagement (Vuong, 2026), perceived usefulness (Kim et al., 2025), and innovation capacity (Zhong et al., 2025). These mechanisms help explain how AI adoption translates into performance outcomes.

5. Theoretical and Empirical AI Models Adapted to Vietnam

Section 5 builds on the conceptual foundations established in the literature review and the theoretical–empirical frameworks. It clarifies how the reviewed studies construct their models, how AI adoption is theorized and operationalized, and how these models can be adapted to the Vietnamese context. This section has two goals: (i) to synthesize the dominant theoretical models used across the 56 studies, and (ii) to outline empirical modeling strategies suitable for analyzing AI adoption and its impacts in Vietnam.

5.1. Theoretical Models Used in AI Research

The theoretical models employed in the literature reflect the multidimensional nature of AI adoption. They span economics, organizational behavior, psychology, institutional theory, and sociotechnical studies. Together, they provide a rich conceptual toolkit for understanding how AI reshapes productivity, labor markets, and organizational practices.

Task-based models of automation: A foundational theoretical strand comes from task-based models of automation. Acemoglu and Restrepo (2020) develop a framework in which AI substitutes for routine tasks while complementing non-routine ones. Their model distinguishes between displacement effects (AI replaces labor in specific tasks) and productivity effects (AI increases output and creates new tasks). This framework underpins many empirical studies examining labor-market impacts, including Nguyen and Vo's (2022) cross-country analysis of unemployment and Giwa and Ngepah's (2024) study of low-skilled employment in South Africa.

General-purpose technology (GPT) models: Several studies conceptualize AI as a general-purpose technology whose effects unfold through complementarities, spillovers, and continuous improvement. Steinhoff (2024) and Jin et al. (2025) emphasize that AI represents a qualitative shift from rule-based automation to "synthetic automation", enabling the automation of tasks that cannot be explicitly codified. Zhong et al. (2025) apply this GPT logic to energy efficiency, showing how AI diffuses through manufacturing systems via predictive maintenance and process optimization.

Technology acceptance and behavioural model: In organizational and service-sector studies, adoption is often modelled through behavioural frameworks: (i) TAM (Technology Acceptance Model) — used in Kim et al. (2025) and Thuy et al. (2026) to explain how perceived usefulness and ease of use shape adoption intentions, (ii) TOEP (Technology–Organization–Environment–Personal) — integrated with TAM by Kim et al. (2025) to capture multi-layered determinants of AI acceptance, (iii) JD-R (Job Demands–Resources) Model — used by Vuong (2026) and Pham & Pham (2026) to explain how AI functions as a job resource (enhancing engagement) or a job demand (creating identity threat), and (iv) TPB (Theory of Planned Behavior) — extended by Wach et al. (2026) to incorporate AI-related competencies and entrepreneurial identity. These models are particularly relevant for Vietnam's service sectors—education, healthcare, hospitality—where human acceptance is a prerequisite for effective AI integration.

Institutional and governance models: Institutional theory plays a central role in studies examining AI adoption within regulated environments. Tong and Tan (2026) adapt the Double Helix framework, conceptualizing climate resilience as emerging from the co-evolution of institutional pressures and technological capabilities. Their model shows how regulatory expectations and AI capability reinforce each other, a dynamic highly relevant for Vietnam's public-sector digital transformation.

Sociotechnical and ethical models: Several studies adopt sociotechnical perspectives to understand how AI interacts with social norms, identities, and moral expectations. Lee et al. (2026) use actor-network theory to analyze teacher imaginaries of AI textbooks, while Choroszewicz (2026) applies the concept of moral crumple zones to public-sector AI adoption. Eriksson et al. (2026) introduce a predictive moral framework to explain public acceptance of AI based on moral intuitions. These models highlight that AI adoption is not purely technical but embedded in social, ethical, and cultural contexts—an insight crucial for Vietnam's diverse and rapidly changing society.

5.2. Empirical Models Used in AI Research

The empirical literature employs a wide range of econometric, statistical, and machine-learning models. These methods reflect the heterogeneity of AI applications across sectors and the diversity of available data.

Econometric Models: Econometric approaches dominate studies examining macroeconomic and labour-market impacts. The frequently employed approaches include: (i) Fixed-effects panel regressions — used by Zhong et al. (2025) to estimate AI's effect on energy intensity, (ii) Instrumental variables (IV) — used by Tong and Tan (2026) to address endogeneity in AI capability, (iii) Difference-in-differences (DiD) — used by Tong and Tan (2026) to exploit China's 2018 Environmental Tax Reform as an exogenous shock, (iv) Panel Smooth Transition Regression (PSTR) — used by Nguyen and Vo (2022) to model nonlinear AI–unemployment relationships, and (iv) Vector Error Correction Models (VECM) — used by Giwa and Ngepah (2024) to examine long-run relationships between AI investment and low-skilled employment. These models are well-suited for analyzing Vietnam's sectoral data, especially in manufacturing, energy, and labor markets.

Structural Equation Modelling (SEM): SEM is widely used in organizational and behavioural studies: (i) Partial Least Squares SEM — used by Cao & Nguyen (2025), Afifa et al. (2024), and Vuong (2026) to model complex relationships involving perceptions, readiness, identity, and performance, and (ii) MASEM (Meta-Analytic SEM — used by Kim et al. (2025) to synthesize findings across 26 studies. SEM is particularly relevant for Vietnam's service sectors, where psychological and organizational variables mediate AI adoption.

Machine-Learning and Hybrid Models: Technical and environmental studies rely heavily on ML/DL models: (i) Random Forest, XGBoost, SVM — used in air-quality forecasting (Chadalavada et al., 2025) and environmental modeling (Guo et al., 2025), (ii) LSTM, CNN-LSTM hybrids — used in wastewater treatment, hydrological forecasting, and environmental monitoring, and (iii) Edge-AI optimization pipelines — used by Nguyen & Nguyen (2026) for real-time anomaly detection in power-transmission corridors. These models demonstrate AI's operational value in agriculture, energy, and environmental management—key sectors for Vietnam.

Bibliometric and Scientometric Models: Several studies use bibliometric mapping to analyse research trends: Baarimah et al. (2024) on wastewater treatment, Nettey et al. (2026) on AI in entrepreneurship, and Dreksler et al. (2025) on public attitudes toward AI. These methods help identify knowledge gaps and emerging themes relevant for Vietnam's research ecosystem.

Qualitative and Mixed-Methods Models: Qualitative approaches provide insight into human experiences and institutional dynamics: Digital ethnography (Choroszewicz, 2026), Sociotechnical imaginaries (Lee et al., 2026), and Content analysis of public discourse (Thaiduong, 2026; Wang & Liang, 2024). These methods are essential for understanding AI adoption in Vietnam's public sector, education, and healthcare.

5.3. A Proposed Theoretical–Empirical Model for Vietnam

Drawing on the reviewed literature, a unified model for analyzing AI adoption in Vietnam should integrate: (i) Technological capability: AI infrastructure, data readiness, digital transformation, and sector-specific technologies. (ii) Organizational capability:

leadership, HR readiness, digital competence, and absorptive capacity. (iii) Human factors: skills, identity, trust, acceptance, and psychological readiness. (iv) Institutional environment: regulation, national AI strategy, governance quality, and policy incentives. (v) Sectoral characteristics: agriculture, manufacturing, services, and public administration each have distinct adoption pathways. (vi) Outcomes: productivity, employment, skills upgrading, innovation, sustainability, and inequality. This integrated model reflects the complexity of AI adoption in an emerging economy and provides a robust foundation for empirical analysis in Section 6.

6. Analysis of the Findings

The synthesis of 56 studies reveals that artificial intelligence is reshaping economic activity across sectors in ways that are both transformative and uneven. For Vietnam, an emerging economy undergoing rapid digitalization, the findings highlight a complex interplay between productivity gains, labor-market restructuring, skill transformation, competitiveness pressures, and institutional readiness. This section integrates global evidence with Vietnam's sectoral context to analyze how AI is influencing the future of work, productivity, supply chains, and economic upgrading, while also identifying the opportunities, risks, and policy challenges that accompany this transition.

AI as a Productivity and Growth Tool: In the literature, AI consistently emerges as a powerful driver of productivity. Zhong et al. (2025) show that AI reduces energy intensity in manufacturing, especially in middle-income economies—precisely where Vietnam is positioned. Fernandes and DMello (2025) demonstrate that AI-enabled aquaculture systems improve feed efficiency, disease detection, and biomass estimation, that directly relevant to Vietnam's seafood export sector. Nguyen and Nguyen (2026) show that edge-AI systems enhance infrastructure reliability through real-time anomaly detection.

These findings collectively indicate that AI can help Vietnam move beyond labor-intensive growth toward technology-enabled productivity upgrading, supporting the country's ambition to climb global value chains. AI's contributions to predictive maintenance, quality control, logistics optimization, and environmental monitoring also strengthen Vietnam's competitiveness in manufacturing, agriculture, and services.

Labour Market Impacts and the Future of Work: The literature provides strong evidence that AI reshapes labor markets through both substitution and complementarity. Acemoglu and Restrepo (2020) show that robots displace routine workers, while Giwa and Ngepah (2024) find that AI reduces low-skilled employment in South Africa. Lee (2025) shows that IT investment—including AI—reduces workforce size in Korean firms.

For Vietnam, these findings imply that routine-intensive sectors such as textiles, electronics assembly, retail, and logistics face significant displacement risks. At the same time, AI creates demand for new hybrid roles requiring digital, analytical, and interpersonal skills. Vuong (2026) shows that generative AI enhances job crafting and performance when workers possess sufficient digital competence. The future of work in Vietnam will therefore be characterized by job polarization, with rising demand for high-skill digital roles and declining demand for routine manual and clerical tasks. Without proactive reskilling, the risk of widening inequality is substantial.

Skills Upgrading, Skill Gaps, Reskilling, and Adaptability: A consistent finding in the literature is that skills are the decisive factor determining whether individuals and firms benefit from AI. Wach et al. (2026) show that AI-related competencies shape entrepreneurial identity and intention. Thuy et al. (2026) find that medical students' intention to adopt AI depends on perceived competence and attitudes. Vuong (2026) demonstrates that digital competence amplifies the positive effects of generative AI on job performance.

For Vietnam, where digital literacy remains uneven and many workers lack foundational ICT skills, the findings highlight an urgent need for: large-scale digital upskilling, AI literacy programs, vocational training aligned with AI-enabled industries, and lifelong learning systems employer-supported reskilling pathways. Without these investments, AI adoption may outpace human capability, creating a structural skill gap that limits productivity gains and increases exclusion risks.

Competitiveness and Supply Chain Advancement: AI adoption strengthens competitiveness by enabling firms to optimize production processes, reduce waste and energy use, improve quality control, enhance supply chain visibility, and accelerate innovation cycles. Studies such as Fernandes & DMello (2025), Zhong et al. (2025), and Nguyen & Nguyen (2026) show that AI improves operational efficiency across agriculture, manufacturing, and infrastructure.

For Vietnam, AI can support supply chain upgrading in several ways: real-time logistics optimization for export industries, predictive analytics for supply chain disruptions, AI-enabled traceability systems for agriculture and seafood, automated quality inspection for electronics and textiles, and AI-driven demand forecasting for retail and e-commerce. These capabilities are essential for Vietnam's integration into higher-value segments of global value chains.

Potentials and Opportunities for Vietnam: The reviewed studies highlight several opportunities: productivity gains across agriculture, manufacturing, and services, energy efficiency improvements supporting green growth, enhanced competitiveness in global markets, new high-skill employment opportunities, improved public services through AI-enabled healthcare, education and administration, stronger climate resilience through predictive analytics and environmental monitoring, and faster innovation cycles in SMEs and startups. These opportunities align closely with Vietnam's national AI strategy and digital transformation goals.

Challenges, Risks, and Regulatory Frameworks: Despite its potential, AI adoption also introduces significant challenges: (i) labour-market risks: job displacement, skill mismatches, labour-market exclusion (Lamperti & Castellani, 2026), and fear of automation (Włoch et al., 2025), (ii) organizational barriers: low digital readiness, limited HR capability (Cao & Nguyen, 2025), and weak leadership support (Afifa et al., 2024), (iii) institutional and governance gaps: insufficient data governance, limited ethical and legal frameworks (Nguyen, 2025), and declining public trust in AI's benevolence and integrity (Thaiduong, 2026), (iv) sector-specific risks: identity threat in service roles (Pham & Pham, 2026), opacity and accountability issues in public-sector AI (Choroszewicz, 2026), and environmental risks from energy-intensive AI systems (Ha, 2025). Vietnam's regulatory frameworks must therefore evolve to address: data protection, algorithmic transparency, accountability mechanisms, ethical guidelines, and sector-specific governance.

Sector-Specific Implications for Vietnam: Agriculture: (i) AI can support precision farming, disease detection, and supply chain transparency, but adoption is limited by rural connectivity and digital literacy. (ii) Manufacturing: AI enhances productivity and energy efficiency but increases displacement risks for routine workers. (iii) Services: AI reshapes customer engagement, administrative tasks, and professional identity, requiring new skill sets and organizational support. (v) Public sector: AI adoption raises concerns about responsibility, transparency, and worker burden, and (vi) Environmental management: AI significantly improves monitoring and forecasting, supporting Vietnam's climate resilience goals.

Conclusion of AI Adoption and Impacts in Vietnam: The findings show that AI offers Vietnam substantial opportunities for productivity upgrading, competitiveness, and supply chain advancement. However, realizing these benefits requires addressing skill gaps, labor-market risks, organizational readiness, and governance challenges. AI's impacts are deeply heterogeneous across sectors, skill groups, and institutional environments, underscoring the need for targeted, sector-specific strategies. The summary of empirical studies on AI adoption and impact categorized by pathways and types of impacts is presented in Appendix Tables 1.A and 1.B, respectively.

7. Summary and Conclusion

This review has synthesized evidence from 56 studies to examine how artificial intelligence is reshaping productivity, labor markets, skills, and sectoral transformation, with a particular focus on the Vietnamese economy. The findings reveal that AI is not a single technology but a constellation of capabilities—machine learning, computer vision, natural language processing, predictive analytics, and autonomous systems—that collectively function as a general-purpose technology with far-reaching economic and social implications. Across global and sector-specific studies, AI consistently emerges as a driver of productivity, efficiency, and innovation, while simultaneously introducing new risks, inequalities, and governance challenges.

A central insight from the literature is that AI's impacts are deeply heterogeneous. Productivity gains are strongest in sectors where digital infrastructure, data availability, and technological readiness are sufficiently developed. Studies such as Zhong et al. (2025), Fernandes and DMello (2025), and Nguyen and Nguyen (2026) demonstrate that AI enhances energy efficiency, operational reliability, and process optimization across manufacturing, aquaculture, and infrastructure. These findings align closely with Vietnam's economic structure, where manufacturing and agriculture remain central to growth and where digital transformation is accelerating.

At the same time, AI introduces significant labor-market disruptions. Evidence from Acemoglu and Restrepo (2020), Giwa and Ngepah (2024), and Lee (2025) shows that AI and automation disproportionately displace routine and low-skilled workers, contributing to job polarization and widening skill gaps. For Vietnam—where a large share of the workforce remains in low-skill or informal employment—these risks are substantial. Without proactive reskilling and social protection, AI adoption may deepen existing inequalities and create new forms of labor-market exclusion, as highlighted by Lamperti and Castellani (2026).

The review also underscores the importance of skills transformation. Studies by Vuong (2026), Wach et al. (2026), and Thuy et al. (2026) consistently show that digital competence, AI literacy, and information-processing skills are decisive in determining whether individuals and organizations benefit from AI. These findings point to an urgent need for Vietnam to invest in digital skills, vocational training, and lifelong learning systems to ensure that workers can adapt to rapidly changing technological demands.

Another major theme concerns organizational readiness and institutional capacity. Research by Cao and Nguyen (2025), Afifa et al. (2024), and Tong and Tan (2026) demonstrate that AI adoption depends not only on technological availability but also on leadership, organizational culture, regulatory frameworks, and institutional pressures. Vietnam's national AI strategy provides a strong foundation, but gaps remain in data governance, ethical guidelines, and sector-specific regulations—particularly in healthcare, education, and public administration.

The review further highlights AI's potential to enhance competitiveness and supply chain advancement. AI-enabled logistics optimization, predictive analytics, traceability systems, and automated quality control can help Vietnam move into higher-value segments of global value chains. These capabilities are essential for sustaining export competitiveness in electronics, textiles, agriculture, and services.

Despite these opportunities, the literature also identifies significant risks and costs. These include job displacement, identity threats in service roles, algorithmic opacity, declining public trust, and the energy demands of AI systems. Studies such as Pham and Pham (2026), Thaiduong (2026), and Ha (2025) show that AI adoption can generate psychological strain, ethical concerns, and environmental pressures if not accompanied by appropriate safeguards.

Overall, the findings suggest that AI offers Vietnam a powerful pathway for productivity upgrading, innovation, and economic modernization—but only if the adoption is accompanied by strategic investments in human capital, institutional capacity, and inclusive governance. The country's ability to harness AI's benefits while mitigating its risks will depend on coordinated efforts across government, industry, education, and civil society.

In conclusion, AI is poised to play a central role in Vietnam's transition toward some knowledge-based, innovation-driven economy. The evidence reviewed in this paper demonstrates both the transformative potential of AI and the structural challenges that must be addressed to ensure equitable and sustainable adoption. As Vietnam continues to implement its national AI strategy, the insights from global and sector-specific research provide a critical foundation for designing policies that support productivity growth, protect workers, strengthen competitiveness, and promote inclusive development. The next section outlines key directions for future research to deepen understanding of AI's evolving role in Vietnam's economic transformation.

8. Direction of Future Research

Future research on AI in Vietnam should move beyond broad global patterns and focus on questions that reflect the country's unique economic structure and development trajectory. A key priority is to strengthen causal evidence, using policy reforms—such as national AI strategies, digital-transformation mandates, and sector-specific regulations—as natural experiments to identify how AI influences wages, employment, productivity, and firm competitiveness.

The future of work remains a central research frontier. Vietnam's labour market, shaped by a large low-skilled workforce and high informality, requires deeper analysis of job polarization, transitions from routine to non-routine work, gendered impacts, and the vulnerabilities of informal and inter-provincial migrant workers. Psychological dimensions—including identity threat, fear of automation, and worker adaptability—also deserve closer attention.

Research on skills and human capital is equally important. Little is known about how Vietnamese workers build AI-related competencies, how effective current training programs are, or how education systems can integrate AI literacy. Studies on lifelong learning, vocational training, and barriers to reskilling—especially in rural areas—would provide valuable insights.

More sector-specific studies are needed to understand distinct AI adoption pathways in agriculture, manufacturing, services, and public administration. These sectors face different opportunities and constraints related to supply-chain upgrading, export competitiveness, environmental resilience, and public-sector accountability.

Finally, future work should address governance and ethics, including data governance, transparency, and public trust. Comparative ASEAN studies and empirical research on citizen perceptions would help inform Vietnam's evolving regulatory frameworks.

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Appendix Table 1.A Summary of empirical studies on AI adoption and impacts categorized by impact pathways.

Impact Pathway	Representative Studies	Focus & Methods	Core Findings	Relevance for Vietnam
AI Applications Across Sectors	Fernandes & DMello (2025); Huda et al. (2026); Guo et al. (2025); Chadalavada et al. (2025); Nguyen & Nguyen (2026); Omer et al. (2026)	ML/DL models; computer vision; edge AI; sector-specific datasets	AI improves aquaculture, agriculture, water systems, waste management, air-quality forecasting, energy systems, and infrastructure monitoring	Directly applicable to Vietnam's agriculture, aquaculture, energy, environment, and infrastructure modernization
Labour Market Impacts	Acemoglu & Restrepo (2020); Giwa & Ngepah (2024); Lee (2025); Lamperti & Castellani (2026); Włoch et al. (2025)	Macro labour models; VECM; FE; worker surveys	AI displaces routine workers; increases unemployment in low-skill segments; raises exclusion risks; fear of automation widespread	Highlights risk for Vietnam's large low-skill workforce and informal sector
Future of Work & Skills Transformation	Vuong (2026); Pham & Pham (2026); Wach et al. (2026); Thuy et al. (2026); Liu (2025)	SEM; JD-R; TAM; mixed methods	Digital competence amplifies AI benefits; AI reshapes job crafting, identity, and engagement; skill gaps widen without reskilling	Supports Vietnam's need for AI literacy, vocational training, and lifelong learning
AI as a Productivity & Growth Tool	Zhong et al. (2025); Ha (2025); Wen et al. (2025); Fernandes & DMello (2025)	National panels; FE, IV, PSTR; sectoral performance metrics	AI improves productivity, energy efficiency, process optimization, and operational reliability; supports green growth	Strong potential for Vietnam's industrial upgrading and sustainable development
Competitiveness & Innovation Impacts	Tong & Tan (2026); Cao & Nguyen (2025); Afifa et al. (2024); Kim et al. (2025)	Firm surveys; PLS-SEM; MASEM; institutional theory	Leadership, readiness, and institutional pressures drive AI capability; AI enhances innovation, quality, and competitiveness	Critical for Vietnam's SMEs, export industries, and digital-transformation agenda
Supply Chain & Value Chain Advancement	Fernandes & DMello (2025); Nguyen & Nguyen (2026); Huda et al. (2026)	Technical performance models; predictive analytics; edge AI	AI improves traceability, logistics optimization, predictive maintenance, and risk management	Supports Vietnam's integration into higher-value global value chains
Governance, Ethics & Public Trust	Thaiduong (2026); Bao et al. (2022); Wang & Liang (2024); Eriksson et al. (2026); Teo (2024)	Public surveys; LCA; content analysis; ethnography	Trust in AI's ability is high but trust in integrity/benevolence declining; moral intuitions shape acceptance; concerns about manipulation	Essential for Vietnam's AI governance, public-sector adoption, and trust-building

Appendix Table 1.B Summary of empirical studies on AI adoption and impacts categorized by type of impact.

Impact Category	Representative Studies	Focus & Methods	Core Findings	Relevance for Vietnam
Productivity, Efficiency & Economic Growth	Zhong et al. (2025); Fernandes & DMello (2025); Nguyen & Nguyen (2026); Ha (2025); Wen et al. (2025)	National panels; sectoral datasets; ML/DL; FE, IV	AI improves productivity, energy efficiency, process optimization, and operational reliability; supports green growth	Strong potential for industrial upgrading, aquaculture modernization, and infrastructure efficiency
Labour Market, Skills & Future of Work	Acemoglu & Restrepo (2020); Giwa & Ngepah (2024); Vuong (2026); Pham & Pham (2026); Włoch et al. (2025); Lamperti & Castellani (2026)	Worker surveys; SEM; JD-R; mixed methods; macro labour models	AI displaces routine workers; increases job polarization; digital competence moderates positive effects; identity threat and fear of automation widespread	Highlights urgent need for reskilling, AI literacy, and protection for vulnerable workers
Organizational Adoption, Readiness & Capability	Cao & Nguyen (2025); Afifa et al. (2024); Kim et al. (2025); Tong & Tan (2026)	Firm surveys; PLS-SEM; MASEM; institutional theory	Perceived usefulness, leadership, HR readiness, and institutional pressures shape adoption; organizational culture mediates outcomes	Critical for SME digital transformation, HR modernization, and public-sector adoption
Sector-Specific Technological Applications (Agriculture, Manufacturing, Environment, Energy)	Huda et al. (2026); Guo et al. (2025); Chadalavada et al. (2025); Omer et al. (2026); Fernandes & DMello (2025)	ML/DL models; computer vision; edge AI; domain-specific datasets	AI enhances precision agriculture, aquaculture, waste management, air-quality forecasting, and energy systems	Directly applicable to Vietnam's agriculture, aquaculture, energy, and environmental governance
Public Perception, Trust, Ethics & Governance	Thaiduong (2026); Bao et al. (2022); Wang & Liang (2024); Eriksson et al. (2026); Teo (2024)	Public surveys; LCA; content analysis; ethnography	Trust in AI's ability is high but trust in benevolence/integrity declining; moral intuitions shape acceptance; concerns about manipulation and accountability	Essential for ethical AI policy, public-sector deployment, and building citizen trust
Education, Healthcare & Human-Centered AI	Thuy et al. (2026); Nguyen et al. (2025); Lee et al. (2026); Bal & Arseven (2026)	Student/teacher surveys; SEM; ANT; systematic reviews	AI literacy remains low; teachers anticipate both opportunities and disruptions; AI supports personalized learning but risks dependency	Supports reforms in medical education, digital textbooks, and AI-enabled learning