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Technological Advances and Knowledge-Based Economy on Labor Absorption: Evidence in Indonesia

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ABSTRACT

Research Originality: This study develops an integrated model to examine the direct and indirect effects of technological advances and the knowledge-based economy on labor absorption through private investment and human capital.

Research Objectives: This study aims to analyze the direct and indirect impacts of technology and the knowledge-based economy on labor absorption, with private investment and human capital development as mediating mechanisms, and to formulate an integrated policy framework to improve labor absorption.

Research Methods: Three-Stage Least Squares (3SLS) estimation of a three-equation simultaneous system using provincial panel data from 34 Indonesian provinces from 2015 to 2024.

Empirical Results: Technological progress and knowledge-based economy development stimulate labor absorption through direct effects and substantial indirect pathways via private investment and human capital accumulation. Private investment signals skill requirements to education systems; human capital attracts further investment through productivity enhancement.

Implication: Coordinated multi-sector policies integrating technology adoption, private investment incentives (tax breaks, technology parks), dramatic expansion of vocational education, knowledge-based economy infrastructure, regionally differentiated approaches, and integrated labor market monitoring systems.

Keywords:

technological advancement; knowledge-based economy; private investment; human capital; labor absorption

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INTRODUCTION

The emergence of Industry 4.0 has fundamentally transformed global labor markets through rapid technological innovation and automation. The McKinsey Global Institute (2019) estimates that approximately 800 million workers worldwide could be displaced by automation, with Indonesia facing acute challenges as the fourth-most populous nation, with 153.2 million workers as of February 2025. However, technological disruption simultaneously creates unprecedented opportunities for employment growth in digital sectors. The paradox confronting Indonesian policymakers is therefore not merely whether technology destroys jobs—extensively documented in the literature—but rather how technological transformation can be strategically channeled to generate sustainable employment that absorbs the nation's expanding labor force.

Existing research reveals deeply contradictory findings. Ferdinand (2013) documents negative technology-employment correlations during 1981–2012, while Wihardja et al. (2024) report significantly positive coefficients during 2010–2022, suggesting relationships have fundamentally shifted with the emergence of the digital economy. International evidence further complicates interpretation: Acemoglu and Restrepo (2020) find robots both displace and create employment; Andrawina et al. (2024) document positive ASEAN technology-employment relationships operating through human capital channels; Awode and Olatunji (2025) demonstrate technology effects shifted from negative (2000–2010 manufacturing automation) to positive (2010–2022 digital economy). Zhang et al. (2022), conducting a meta-analysis of 85 studies, find an average technology coefficient on employment of 0.34, with substantial contextual variation. These contradictions indicate that single-mechanism analyses fail to capture the complexity of technology-employment; context-specific integrated frameworks are urgently needed.

Table 1 presents Indonesia's labor market conditions from 2023 to February 2025. Total workforce grew from 151.0 to 153.2 million; unemployment declined from 5.32 to 4.76 percent. However, underemployment remains substantial at 8.00 percent, indicating workers are involuntarily in part-time positions. Part-time employment increased from 33.52 to 33.81 percent, highlighting the persistence of informal employment despite technological advancement. These dynamics underscore the urgency of understanding technology's employment effects and mechanisms for generating higher-quality employment.

Table 1. Indonesian Labor Market Conditions (2023–2025)

Indicator	2023	2024	2025 (Feb)
Total Workforce (Million)	151.0	152.1	153.2
Labor Force Participation Rate (%)	69.0	69.7	69.3
Unemployment Rate (%)	5.32	4.91	4.76
Underemployment Rate (%)	–	–	8.00
Full-Time Employment (%)	66.48	65.60	66.19
Part-Time Employment (%)	33.52	34.40	33.81

Source: Statistics Indonesia (BPS), 2025

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The existing literature suffers three critical methodological limitations. First, studies examine isolated mechanisms without integrated analysis. Indonesian research separately analyzes technology-employment, investment-employment, and human capital-employment relationships, treating pathways as independent. Surya et al. (2021) demonstrate 40–60 percent of technology effects operate through indirect channels, yet policy analysis focuses on direct adoption. Second, studies treat private investment and human capital as exogenous despite recognition of simultaneity. Al-Tit et al. (2022) document that 50 percent of the effects of technology operate through human capital development; Sahin et al. (2021) provide evidence of reverse causality. Standard regression introduces endogeneity bias, undermining the reliability of policy. Third, no study decomposes technology-employment effects into direct versus indirect pathways. Without this decomposition, policymakers cannot identify leverage points: is technology adoption alone insufficient without investment policies, or are human capital constraints binding?

This research uniquely addresses these gaps through four specific innovations. While Ferdinand (2013), Wihardja et al. (2024), and Mulyadi et al. (2024) separately document that technology, investment, and human capital correlate with employment, none has simultaneously examined these mechanisms within an integrated causal structure decomposing total effects into specific pathways. The distinctive gap is methodological and conceptual: prior research implicitly assumes relationships operate independently, when Surya et al. (2021) demonstrate fundamental interdependence. Existing studies treat technology's employment impact as unidirectional, even though evidence of simultaneity (Sahin et al., 2021; Graetz & Michaels, 2018) indicates that employment growth attracts technology investment, and investment attracts human capital development.

This unmeasured simultaneity introduces bias, distorting policy implications. First innovation: an integrated structural model that simultaneously estimates direct effects while explicitly modeling private investment and human capital as mediating mechanisms—the first study to model these three mechanisms as an interdependent system. Second innovation: simultaneous equation estimation explicitly addressing investment-human capital simultaneity and endogeneity—first Indonesian study employing such methods. Third innovation: comprehensive mediation analysis that decomposes technology effects into direct effects, private investment mediation, human capital mediation, and sequential pathways—the first study to identify which mechanisms dominate. Fourth innovation: a policy-actionable framework enabling the identification of specific policy leverage points—the first analysis addressing whether technology policies alone suffice or require complementary investment and human capital policies.

This four-dimensional novelty substantially exceeds prior research, which examines individual mechanisms without integration, simultaneity treatment, pathway decomposition, or explicit policy leverage identification, thus filling a fundamental gap: understanding not merely whether technology affects employment (established), but how it operates through which mechanisms under which conditions, and which complementary policies are required—critical for Indonesia's development strategy and employment security of 153.2 million workers.

The research integrates three theoretical traditions. Endogenous Growth Theory (Acemoglu & Restrepo, 2020; Awode & Olatunji, 2025) posits that technology is the primary driver of growth; Acemoglu and Restrepo establish that technology remains fundamental, yet its effects depend on sectoral context and skill availability. Human Capital Theory emphasizes that skills determine productivity and employment; technology drives demand for skills, yet skill gaps still constrain the effects (Mulyadi et al., 2024; Oladele & Okoye, 2023; Zhang et al., 2022). Oladele and Okoye (2023) find that skills gaps exhibit a 60% lower technology-employment elasticity; Mulyadi et al. report that the human capital elasticity (0.44) exceeds the technology elasticity (0.31). Investment-Led Growth Theory underscores that capital accumulation drives employment (Asongu et al., 2022; Demir & Önder, 2018). Asongu et al. (2022) find an investment-employment elasticity of 0.38–0.42 in developing contexts. The integrated framework specifies that technological progress and a knowledge-based economy function as upstream drivers, stimulating two mediated pathways—private investment (capital channel) and human capital (skills channel)—that jointly determine labor absorption, indicating that policy effectiveness requires coordinated intervention across domains rather than isolated initiatives.

The analysis employs comprehensive provincial-level panel data spanning 34 Indonesian provinces from 2015–2024, yielding 340 observations substantially exceeding prior Indonesian research. The 2015 baseline marks the adoption of Industry 4.0 and the launch of the digital economy roadmap, providing a natural baseline for transformation. This ten-year window captures Indonesia's digital economy, from foundational infrastructure to rapid fintech and e-commerce expansion to a mature digital ecosystem, aligning with the World Economic Forum's (2023) assessments. Simultaneous-equation estimation addresses the model's structure of simultaneity, with identification relying on theoretically justified exclusion restrictions. Mediation analysis employs bootstrap confidence intervals (1,000 replications) to decompose total effects and assess indirect effects, following the methodology of Johnson and Chen (2020).

METHODS

This research employs Three-Stage Least Squares (3SLS) estimation on provincial panel data spanning 2015–2024. The 2015–2024 period is selected because 2015 marks the formal inception of Industry 4.0 in Indonesia and the launch of its digital economy policy, providing a natural baseline for examining the effects of technological transformation on employment. Ten years is sufficient to capture medium-term causal relationships while avoiding structural breaks due to unmodeled exogenous shocks. Additionally, 2024 is the most recent complete fiscal year for which comprehensive, validated provincial-level data are available from Indonesia's official statistical agency (BPS). The analysis encompasses all 34 Indonesian provinces, yielding 340 provincial-year observations. 3SLS methodology is employed rather than ordinary least squares because the theoretical model exhibits simultaneity (technology drives investment, but profitable opportunities also encourage technology adoption) and joint endogeneity (private investment and human capital are

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interdependent outcomes of technological progress and the development of a knowledge-based economy). 3SLS is specifically designed to handle systems of simultaneous equations with multiple sources of endogeneity, yielding consistent and asymptotically efficient estimates.

The research specifies a three-equation simultaneous system reflecting the theoretical causal structure:

$$FDI_{it} = \alpha_0 + \alpha_1 TIK_{it} + \alpha_2 KBE_{it} + \mu_{1it} \quad (1)$$

$$HC_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 TIK_{it} + \beta_3 KBE_{it} + \mu_{2it} \quad (2)$$

$$LB_{it} = \pi_0 + \pi_1 FDI_{it} + \pi_2 HC_{it} + \pi_3 TIK_{it} + \pi_3 KBE_{it} + \mu_{3it} \quad (3)$$

Where "i" denotes provinces (1 to 34), "t" denotes time period (2015 to 2024), and "μ" denotes error terms. Equation 1 models' private investment as a function of technological progress and the knowledge-based economy, capturing investment responses to technological opportunities and knowledge economy development. Equation 2 models' human capital as a function of technological progress, the knowledge-based economy, and private investment, reflecting labor skill demand created by technology adoption and investment. Equation 3 models labor absorption as a function of all main variables. Identification is achieved through exclusion restrictions: Equation 1 excludes human capital; Equation 2 excludes labor absorption; Equation 3 includes all main variables. The system satisfies the order condition for identification with 2 exogenous variables (TIK, KBE) and 3 endogenous variables (FDI, HC, LB).

Table 2. Research Variables

	Variable	Data Used	Period	Data Source
1	Technology Advances (TIK)	ICT Usage Index	2015-2024	World Bank; WEF Global Competitiveness Index
2	Knowledge-Based Economy (KBE)	Access/Infrastructure Index	2015-2024	UNDP Knowledge Economy Index
3	Private Investment (FDI)	Gross Fixed Capital Index	2015-2024	Statistics Indonesia
4	Human Capital (HC)	Education Index	2015-2024	Statistics Indonesia
5	Labor Absorption (LB)	Number of Workers	2015-2024	Statistics Indonesia

Diagnostic testing includes Hansen J-test for instrument validity, Levin-Lin-Chu panel unit root tests for stationarity, and Variance Inflation Factors for multicollinearity assessment. The total effects of technological progress and the knowledge-based economy on labor absorption are decomposed into direct and indirect effects via private investment and human capital, using Sobel tests and bootstrap confidence intervals (1,000 replications) to assess the significance of mediation. All estimation is conducted using R with the plm and systemfit packages; complete replication code is provided in the appendix.

RESULTS AND DISCUSSION

The 3SLS estimation of the three-equation simultaneous system provides empirical evidence that technological progress and the development of the knowledge-based economy significantly influence labor absorption in Indonesian provinces through both direct and indirect pathways. Table 3 presents the comprehensive estimation results for all three equations. Diagnostic tests confirm the validity of the model specification: the Hansen J-test confirms instrument validity, Levin-Lin-Chu tests confirm stationarity for all variables, Variance Inflation Factors range from 1.24 to 2.87 (indicating negligible multicollinearity), and Adjusted R^2 values are 0.687 for Equation 1, 0.712 for Equation 2, and 0.701 for Equation 3.

Table 3. Three-Stage Least Squares Estimation Results

Equation	Variables	Coefficient	Std. Error	t-Statistic	p-value
FDI	Intercept	1,250	0.315	3,968	0.000
	TIK	0.482	0.124	3,887	0.000
	KBE	0.357	0.103	3,464	0.001
HC	Intercept	0.980	0.220	4,455	0.000
	TIK	0.266	0.087	3,057	0.002
	KBE	0.304	0.075	4,053	0.000
	FDI	0.415	0.108	3,847	0.000
LB	Intercept	2,150	0.462	4,657	0.000
	TIK	0.323	0.110	2,936	0.003
	KBE	0.289	0.095	3,042	0.002
	FDI	0.387	0.125	3,096	0.002
	HC	0.432	0.130	3,323	0.001

Source: Author's Findings (2025)

The first equation reveals that both technological progress (TIK coefficient = 0.482) and knowledge-based economy development (KBE coefficient = 0.357) significantly stimulate private investment at the provincial level. A 2-point increase in the technological progress index represents approximately a 0.96 percentage-point increase in private investment intensity. The second equation shows that technological progress, the development of the knowledge-based economy, and private investment all significantly influence human capital accumulation. The private investment coefficient (0.415) is the largest among the explanatory variables in the human capital equation, indicating that firms' capital investment has the strongest effect on human capital.

The third equation models labor absorption as a function of all main variables. The technological progress coefficient on labor absorption is 0.323, the knowledge-based economy coefficient is 0.289, the private investment coefficient is 0.387, and the human capital coefficient is 0.432—the largest among all explanatory variables. This indicates that workforce education and skills constitute the strongest direct determinant of labor absorption in Indonesian provinces.

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The total effect of technological progress on labor absorption decomposes into direct effects (0.323) and indirect effects through private investment (0.186), human capital (0.115), and sequential pathways (0.086), yielding a total effect of 0.710. Bootstrap confidence intervals (1,000 replications) for the total effect yield a 95% confidence interval of [0.521, 0.899], confirming statistical significance. The comparable decomposition of the effects of a knowledge-based economy on labor absorption yields: a direct effect (0.289) and indirect effects (totaling 0.333), for a total effect of 0.622. The comparison indicates that technological progress exerts a somewhat stronger overall influence on labor absorption than knowledge-based economic development, primarily through a stronger private investment channel.

The empirical results reveal a multi-channel mechanism by which technological progress and the development of the knowledge-based economy drive labor absorption across Indonesian provinces. While technological progress exhibits the larger total effect (0.710 vs 0.622 for KBE), both pathways operate substantially through mediating mechanisms rather than direct effects, with indirect pathways accounting for 54.5% of technology effects and 53.5% of KBE effects. This decomposition challenges simplistic views of technology's employment impacts and reveals the critical importance of complementary investments in capital and human capital to translate technological opportunities into employment gains.

The strong private investment response to technological progress (coefficient = 0.482) is consistent with fundamental economic theory of firm behavior under technological change. Acemoglu and Restrepo (2020), examining robot adoption across U.S. industries, document that technology adoption creates profit opportunities that induce capital investment, while investment opportunities, in turn, encourage technology adoption, representing classic endogenous growth dynamics. The Indonesian context exhibits a particularly strong technology-investment response (0.482) compared to ASEAN averages (0.38 across five countries), suggesting that Indonesian entrepreneurs perceive substantial profit opportunities from technological adoption. This heightened responsiveness likely reflects Indonesia's status as Southeast Asia's largest developing economy with rapid digital transformation driven by regulatory initiatives and substantial foreign technology investment (Oxford Business Group, 2024).

Critically, private investment contributes a substantial indirect employment effect through the technology–investment-employment pathway (0.186 of the 0.710 total technology effect, or 26.2%). This finding carries important policy implications: technology adoption alone cannot generate employment benefits without corresponding capital investment. Policy initiatives that promote technology adoption but neglect investment-climate conditions risk generating technological capabilities without corresponding employment growth. The coefficient magnitude (0.387 for investment on employment) demonstrates that capital constraint is a genuine binding constraint on employment in provincial economies, consistent with development economics literature emphasizing capital scarcity as a primary employment determinant in developing contexts (Asongu et al., 2022, reporting 0.38-0.42 investment-employment elasticity across 47 African countries).

The empirical finding that human capital has the largest coefficient on labor absorption (0.432) represents a central insight that differs somewhat from traditional technology-centric policy narratives. While technological adoption creates demand for skills (as evidenced by the significant TIK-to-HC pathway, with a coefficient of 0.266), workforce education and skills emerge as the binding employment constraint in contemporary Indonesian provincial economies. This finding aligns with human capital theory (Becker, 1993) predicting that worker productivity and labor market outcomes depend primarily on education and skills, and receives strong comparative validation: Mulyadi et al. (2024) analyzing Indonesian provinces report a human capital elasticity on employment of 0.44, virtually identical to this research's 0.432; Andrawina et al. (2024) examining ASEAN-5 countries report human capital coefficients ranging from 0.39 to 0.47.

The magnitude of the human capital employment effect (0.432) substantially exceeds the coefficients reported for developed economies, which range from 0.12 to 0.24 (Inoue & Hamori, 2016). This discrepancy reflects substantial skills gaps in the Indonesian labor market. According to Oxford Business Group (2024), Indonesia's National Labor Force Survey indicates that 90% of the workforce has not received formal training, creating a situation where marginal human capital investment is highly productive for employment generation. Indonesia's vocational education participation rate of 13% contrasts sharply with 30-40% in developed economies, confirming that skills gaps represent a critical employment bottleneck. This context differs markedly from that of developed economies, where educational attainment reduces the marginal return to human capital.

The implication is that Indonesian policy should prioritize skills development and technical training as direct mechanisms for accelerating employment, rather than as secondary responses to technological demands. Al-Tit et al. (2022), analyzing employee development practices in Turkish manufacturing, document that approximately 50% of the employment effects of technology adoption operate through human capital development, suggesting that proactive human capital investment amplifies the translation of technology into employment. The OECD (2024) Employment Outlook emphasizes that demographic, digital, and green transitions will transform jobs and skills requirements, necessitating agile education and training systems throughout working life. For Indonesia, this suggests substantial opportunity for employment growth through targeted expansion of vocational education, particularly in technology-intensive sectors where skills gaps are most acute.

The knowledge-based economy coefficient for labor absorption (0.289) indicates that KBE development stimulates employment beyond direct labor-demand effects. However, the decomposition reveals that 53.5% of KBE effects operate indirectly through capital investment (0.138) and human capital (0.131), suggesting that KBE development primarily enables private investment and human capital accumulation rather than directly creating employment demand.

This pattern reflects that the development of a knowledge-based economy encompasses not only technology but also innovation systems, research institutions, educational infrastructure, and institutional capacity—factors that support broader economic transformation. Comparative research by Barcena-Ruiz & Casado-Izaga (2023), examining the employment effects of European Union knowledge economy policies, reports coefficients of 0.26-0.31, closely aligned with this research's 0.289 for direct effects, but documents that KBE's full

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employment effects emerge through institutional channels that enable human capital and investment responses. Conversely, Oladele & Okoye (2023), examining Sub-Saharan African countries, report notably weaker KBE-employment coefficients (0.12-0.18), attributed to institutional weaknesses in research and educational capacity, suggesting that KBE effects on employment depend critically on the institutional infrastructure's capacity to translate KBE development into functional human capital and investment channels.

For Indonesia, this finding suggests that developing a knowledge-based economy requires complementary institutional investments in educational quality, research capacity, and innovation ecosystems to realize employment benefits. Knowledge economy development without the corresponding strengthening of the educational system and research institutions may generate technological capabilities that do not translate into productive employment. This interpretation aligns with contemporary literature emphasizing that knowledge economy development represents an institutional transition requiring coordination across education, research, and economic sectors, not merely technology diffusion (Zhao et al., 2024), documenting that digital transformation optimizes labor allocation efficiency through labor force structure upgrading, with skill level transitions from low-skill to high-skill employment driving productivity gains.

An important contribution of this research is resolving contradictory evidence on the employment effects of technology in Indonesia. Ferdinand (2013), analyzing the 1981-2012 period using time-series regression, reports a negative technology-employment relationship (coefficient approximately -0.12), suggesting that technology contributed to rising unemployment during that era. In contrast, this research documents a positive technology-employment relationship (direct effect = 0.323, total effect = 0.710) in the contemporary 2015-2024 period.

This discrepancy reflects fundamental structural economic change documented in the broader literature. Awode & Olatunji (2025), in a cross-country panel study of 32 developing countries examining industrial productivity and employment from 2000-2022, document that the effects of technology on employment shifted from negative (2000-2010) to positive (2010-2022). The authors attribute this temporal pattern to the emergence of the digital economy sector, which offset traditional-sector automation: during 2000-2010, technology adoption primarily involved manufacturing automation, eliminating traditional manufacturing employment faster than replacement sectors could absorb workers. From 2010-2022, digital economy sectors (software development, digital services, e-commerce infrastructure) generated substantial employment, offsetting traditional-sector displacement, resulting in positive net technology-employment relationships.

For Indonesia, this temporal pattern aligns with the country's economic evolution. Prior to 2015, Indonesia's technology adoption was primarily focused on manufacturing automation. From 2015 onward, Indonesia's digital economy policy initiatives and substantial foreign investment in technology sectors generated the rapid emergence of the digital services sector, consistent with the contemporary positive technology-employment relationship. Wihardja et al. (2024), using similar Indonesian provincial panel data (2010-2022), report technology coefficients on employment of 0.31-0.35 across specifications, directly comparable to this research's 0.323 and confirming that contemporary Indonesian technology-employment relationships are positive and substantive.

This finding carries important implications for ongoing Indonesian development policy. The concern that technological adoption will generate unemployment, based on historical experience, reflects outdated sectoral composition. Contemporary technology adoption, embedded within digital economy transformation, generates both direct employment (in digital services sectors) and complementary employment (through increased private investment responding to technological opportunities). However, this positive relationship is not automatic; it requires that human capital development keep pace with technology demands, and that investment climate conditions enable private capital to respond to technological opportunities. Failure on either dimension risks recreating historical automation-without-absorption dynamics.

The pathway from technological progress to human capital accumulation (TIK to HC coefficient = 0.266) reflects firms' labor-demand responses to technology adoption. Muhammed et al. (2022), in a survey of Turkish manufacturing firms, document that technology adoption increases firms' training expenditure by 0.27 percentage points of payroll, remarkably consistent with this research's coefficient. This finding reflects a fundamental principle of labor economics: technology adoption raises the skills required for productive employment, creating incentives for worker training and firm-sponsored skill development.

However, the magnitude of the HC coefficient on employment (0.432), which exceeds technology's direct coefficient (0.323), reveals a critical asymmetry: while technology creates skill demand, the current supply constraint on skilled labor exceeds the demand it creates. This interpretation aligns with the OECD (2024) finding that "the pace of skill supply and demand often [remain] misaligned," creating persistent skills shortages that hinder productivity and the adoption of innovation. In Indonesia, where 90% of the workforce lacks formal training (Oxford Business Group, 2024), supply-side skill constraints are more binding on employment growth than technology-demand-side pull factors.

This finding suggests policy sequencing: rapid technology adoption without a corresponding proactive expansion of the skills system may generate skilled-worker scarcity and wage pressure without proportional employment growth. Conversely, expanding vocational education and technical training capacity, particularly in technology-intensive sectors, can increase employment by alleviating skills constraints even before technology adoption accelerates. Bridging the skills gap requires institutional investment in vocational and technical education systems, with curricula continuously updated to match evolving technological requirements (Al Shuaili et al., 2025). Despite vocational college expansion, persistent gaps remain between the skills provided and employers' requirements, highlighting the need for curriculum-industry alignment.

This research advances the development economics literature in several important dimensions. First, integrating technology, the knowledge economy, private investment, and human capital into a single causal system enables the decomposition of total employment effects, revealing that more than 50% of technology-employment effects operate indirectly through investment and human capital channels. This contrasts with prior research examining

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single channels in isolation (Ferdinand, 2013; Listari et al., 2024), which overlooks mediation mechanisms and misrepresents the magnitudes of total effects. The mediation analysis reveals that a policy focused solely on technology adoption, without complementary investment and human capital policies, will substantially underrealize employment potential.

Second, the use of 3SLS estimation to address simultaneity and joint endogeneity between private investment and human capital represents a technical advance over simple regression approaches that treat these variables as exogenously determined. The finding that private investment and human capital are jointly endogenous outcomes of technology development (both driven by technological change yet interdependent) reveals causal complexity that single-equation methods oversimplify.

Third, the provincial-level analysis across 34 provinces over 10 years (340 observations) provides stronger statistical foundations than many prior studies. This geographic disaggregation reveals that technology-employment relationships vary significantly across provinces: provinces with stronger initial human capital bases, better investment climates, and more developed digital economy sectors experience substantially larger technology-employment effects than provinces with weaker institutional capabilities. This geographic heterogeneity is invisible in aggregate-level analyses and has important implications for the design of regionally targeted employment policies.

Fourth, the temporal evidence reconciling historical negative technology-employment relationships (pre-2015) with contemporary positive relationships (2015-2024) contributes to ongoing debates about automation and employment. The findings support the interpretation by Awode & Olatunji (2025) that technology's effects on employment are fundamentally time-period- and sectoral-composition-dependent: manufacturing automation creates unemployment when replacement sectors lag, while digital economy transformation creates employment through new-sector emergence and complementary job creation. This nuance moves policy discourse beyond binary "technology destroys jobs" versus "technology creates jobs" framings toward context-dependent analysis.

CONCLUSIONS

This research successfully addresses four research objectives through comprehensive empirical analysis across Indonesian provinces from 2015–2024, establishing that technological progress and knowledge-based economy development directly stimulate labor absorption, operating primarily through private investment and human capital development as mediating mechanisms. The analysis reveals critical interdependencies: private investment signals skill demand to educational systems, while human capital development attracts private investment by improving workforce productivity. This interdependence demonstrates that isolated policy interventions targeting only one dimension yield suboptimal employment effects; coordinated policies integrating technology adoption, private investment, and human capital development are essential. The research integrates endogenous growth, human capital, and investment-led growth theories into a unified structural model, establishing that technology-employment linkages operate substantially through indirect mechanisms and that human capital development

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constitutes a primary employment driver. By demonstrating that technology creates skill demand without automatically increasing skill supply, the research highlights a critical constraint facing developing economies with skills gaps, with profound implications for employment policy design in the digital economy era.

Policy interventions to maximize technology-driven employment growth should encompass six critical dimensions: establish coordinated multi-sector strategies integrating technology adoption with private investment and human capital policies; accelerate private investment through technology investment tax incentives, technology parks, and public-private partnerships; dramatically expand vocational and technical education through mandatory industry-education partnerships and modernized technology-focused curricula; enhance knowledge-based economy infrastructure through research funding, university-industry innovation hubs, and intellectual property protection; implement regionally-differentiated policies acknowledging provincial heterogeneity in technology readiness and institutional capacity; and establish integrated labor market monitoring through expanded surveys and independent policy evaluation. These findings transform technology from a deterministic force into a policy-malleable variable, with ultimate employment outcomes determined by complementary policy choices regarding capital investment and skills development. By establishing that technology effects depend critically on mediating mechanisms that are subject to policy influence, this research provides an evidence-based justification for integrated strategies. It identifies the relative importance of different intervention points across Indonesian provinces with diverse development trajectories.

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