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Do Workers with Digital Competencies Earn Higher Wages? Evidence from the Indonesian Labor Market"

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Abstract

This study examines the impact of digital skills on workers' wages in Indonesia using microdata from the 2024 National Labor Force Survey (SAKERNAS) and applying Ordinary Least Squares (OLS) methods. The results reveal a significant digital skill premium. The workers using the internet, digital technologies, or employed in digital-intensive occupations earn higher wages than non-digital workers. The premium is greater among male, formal sector, and mid-generation (Gen X and Millennials) workers, and increases toward the upper wage quantiles. These findings highlight the need for inclusive upskilling and reskilling programs to ensure equitable benefits from digital transformation.

Keywords:Digital Skill, Wage, Labor, Sakernas, Indonesia

INTRODUCTION

The rapid advancement of digital technologies over the past three decades has fundamentally restructured labor markets worldwide, altering the nature of work, the composition of skill demand, and the distribution of wages. The proliferation of information and communication technologies (ICT), automation, artificial intelligence (AI), and the broader digitalization of economic activities has generated a growing premium for workers possessing digital competencies, a phenomenon extensively theorized under the framework of skill-biased technological change (SBTC) (Acemoglu & Autor, 2011; Falck et al., 2021). As digital tools permeate virtually every sector of the economy, the capacity to use, adapt to, and leverage digital technologies has emerged as one of the most

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consequential determinants of individual labor market outcomes, encompassing not only employment probability but also occupational mobility and earnings trajectories (OECD, 2025).

Empirical evidence from advanced economies consistently demonstrates a substantial wage premium associated with digital competencies. Research by the National Skills Coalition in partnership with the Federal Reserve Bank of Atlanta (2023), drawing on an analysis of over 43 million online job postings, found that 92 percent of jobs in the United States require some form of digital skill, and workers qualifying for positions requiring even a single digital competency earn an average of 23 percent more annually compared to workers in roles requiring no digital skills. Critically, the analysis reveals a monotonically increasing relationship: as the breadth and depth of digital skill requirements in a job rise, so too does median hourly compensation (Federal Reserve Bank of Atlanta, 2023). These findings are consistent with Acemoglu and Autor's (2011) task-based framework, which predicts that technological change disproportionately augments the productivity of high-skill workers performing non-routine, cognitive tasks, precisely the tasks most closely associated with digital work.

The theoretical underpinnings of this relationship draw primarily from two complementary traditions in labor economics. First, human capital theory, pioneered by Becker (1962) and formalized by Mincer in (1974), posits that investments in education, training, and skills increase worker productivity and, consequently, market wages. The Mincerian earnings equation, which expresses the logarithm of wages as a linear function of years of schooling and a quadratic function of labor market experience, has served as the canonical empirical framework for estimating returns to human capital across more than a century of scholarship (Deming, 2022; Psacharopoulos & Patrinos, 2018). In this tradition, digital competencies can be conceptualized as a form of human capital whose acquisition entails costs (in time, effort, and resources) and yields returns in the form of enhanced productivity and wage growth. Second, the SBTC hypothesis provides a complementary macro-level explanation: technological advances are not neutral but instead disproportionately increase the relative productivity and demand for skilled labor, thereby expanding the wage differential between skilled and unskilled workers (Autor et al.,2003). The digitalization wave of the 21st century represents perhaps the most pronounced manifestation of SBTC in economic history, with AI and machine learning engineers in 2025 commanding salary growth rates approximately 4.4 percent above the industry average, even as broader technology wage growth has moderated (Robert Half, 2026).

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While the digital wage premium has been extensively documented in high-income economies, considerably less attention has been directed toward understanding its magnitude and determinants in developing countries, where labor market institutions, skill supply constraints, and the digital infrastructure environment differ substantially from those in the Global North. This gap in the literature is consequential: returns to schooling tend to be higher in low- and middle-income countries, where educated workers are relatively scarce (Psacharopoulos & Patrinos, 2018; Hanushek, 2013), suggesting that the wage premium for scarce digital competencies may be even larger in these contexts. Moreover, the trajectory of digitalization in emerging economies is qualitatively distinct, characterized by the simultaneous expansion of digital infrastructure and the coexistence of large informal sectors, significant rural-urban divides, and heterogeneous access to digital devices and connectivity. Evidence from SBTC studies in developing countries corroborates that technological diffusion, particularly through foreign direct investment (FDI) and imported technologies, substantially amplifies the demand for skilled labor and exacerbates wage inequality, even within nations at intermediate stages of development (Berman et al., 2005; Chen et al., 2010).

Indonesia constitutes a particularly compelling and policy-relevant setting in which to examine the relationship between digital competencies and wages. As the world's fourth most populous nation and Southeast Asia's largest economy, Indonesia has experienced rapid and transformative digital growth: internet penetration reached 79 percent in 2024, with over 180 million smartphone users, and the country has emerged as a regional leader in fintech innovation and digital platform economies, exemplified by the rise of technology unicorns such as Gojek and Tokopedia (Department of Commerce, 2025). The Indonesian government has articulated ambitious digital transformation targets under its Making Indonesia 4.0 and Golden Indonesia 2045 strategic frameworks, with the World Bank estimating a demand for an additional 9 million digital workers by 2030 to sustain the trajectory of the digital economy (Department of Commerce, 2025). In response, the Ministry of Communication and Digital Affairs (KOMDIGI) has launched the Digital Talent Scholarship (DTS) program, targeting the training of more than 100,000 professionals annually in high-demand fields including artificial intelligence, cybersecurity, and data analytics.

Despite this rapid expansion, Indonesia confronts a pronounced digital skills gap that threatens both economic efficiency and distributional equity. Analyses of the Sakernas (National Labor Force Survey) data reveal that while Indonesia produces a growing supply of ICT-related graduates, at least 2.45 million between 2016 and 2020,

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there is a qualitative mismatch between the competencies of the available workforce and the specific demands of the digital economy (Santoso et al., 2023). Projections indicate that the annual demand for digital occupations will reach approximately 600,000 positions, yet quality and competency constraints risk rendering this numerical surplus insufficient to meet industry requirements (Santoso et al., 2023). This skills mismatch is compounded by stark spatial inequalities: digital job postings and higher compensation are disproportionately concentrated in Jakarta and major urban centers, reinforcing existing patterns of regional economic divergence (Hidayat & Kadir, 2025). The broader trajectory of wage inequality in Indonesia has been shaped by technological change like empirical analyses using the Sakernas survey data for the period 2003–2009 document a significant increase in both the share of educated workers and the skill wage premium, driven by within-industry demand shifts consistent with SBTC (Kis-Katos, Pieters, & Sparrow, 2014; Asian Development Bank, 2014). Gini coefficient estimates rose from 30.0 points in 2000 to 37.8 points in 2010, a period that broadly coincided with the acceleration of technology-intensive and digital investment (ERIA, 2020).

Within Indonesia specifically, the intersection of digital access and labor market outcomes has begun to attract scholarly attention, though comprehensive studies quantifying the individual-level wage premium attributable to digital competencies remain limited. Existing studies in the Indonesian context have largely examined the aggregate relationship between technological change and wage inequality (Kis-Katos et al., 2014), the productivity-earnings nexus (Cambridge Core, 2023), and skills mismatch under digitalization (Springer, 2025), while the causal and distributional effects of digital competency at the individual worker level have remained underexplored. Internationally, studies using household ICT use surveys from emerging economies demonstrate that even basic IT skills significantly increase employment probability, through both higher labor force participation and a greater likelihood of transitioning from unemployment to employment (Ganju et al., 2021, Information Systems Research), suggesting that digital competencies may serve as both a productivity-enhancing investment and an access-enabling gateway to formal employment.

The limited evidence on digital skills and wages in Indonesia creates important gaps for research, policy design, and human capital investment strategy. First, while aggregate studies confirm the presence of a skill premium, individual-level evidence on whether *digital-specific* competencies, as distinct from general education, generate measurable and significant wage returns remains sparse. Second, the heterogeneity of digital wage premiums across gender, educational attainment, sector, and region has not

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been systematically documented using nationally representative survey data. Third, the mechanisms through which digital competencies translate into higher wages, whether through occupational upgrading, sectoral sorting, complementarity with formal education, or direct productivity enhancement, remain empirically unresolved in the Indonesian context. Addressing these gaps is not merely an academic exercise: as Indonesia pursues its digital economy ambitions, understanding the returns to digital competencies is essential for designing evidence-based training programs, educational curricula, and wage policies that promote both growth and equity.

This study aims to fill these gaps by providing the first comprehensive, individual-level empirical analysis of the relationship between digital competencies and wages in the Indonesian labor market. Employing data from the Survei Angkatan Kerja Nasional (Sakernas), Indonesia's National Labor Force Survey conducted by the Central Statistics Agency (BPS), and augmented with measures of digital skill use and ICT access, this paper estimates the wage premium attributable to digital competencies using an augmented Mincerian wage regression framework.

This paper makes a principal contribution to the literature. It provides granular, individual-level evidence on the digital wage premium in Indonesia, disaggregated by key socioeconomic dimensions, offering insights relevant to ongoing policy debates on digital inclusion and equitable growth. Furthermore, methodologically, this study integrates digital competency measures with the Mincerian framework in a manner that distinguishes the returns to digital skills from those to general education and experience, advancing our understanding of the independent contribution of digital human capital to earnings determination. The findings have direct implications for Indonesia's national digital talent development agenda, for employers navigating the digital transformation of the workplace, and for international development institutions seeking to promote inclusive digitalization in emerging markets.

LITERATURE REVIEW

The empirical literature on the wage returns to ICT and digital skills has expanded substantially since the early 2000s. Study frim Garcia-Lazaro et al., (2025) finds that vacancies requiring digital skills offer 5.8 percent higher posted wages within the same occupation while using an XGBoost machine learning model to classify digital skill requirements in job postings. OECD (2025) reports that information-processing skills independently predict wages after controlling for educational attainment, though education captures a wider range of human capital dimensions, including social skills and

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signaling value. Digitalization widens the wage gap between workers at different skill levels, operating through labor misallocation and skill-technology mismatch mechanisms (Lu & Yuan, 2024).

Evidence from developing economies on the relationship between digital competencies and wages is more heterogeneous and context-dependent than findings from advanced economies, reflecting differences in labor market institutions, the composition of employment, digital infrastructure development, and the sectoral structure of the economy. Study from Hjort & Poulsen (2019) finds that positive effects extend even to less-educated workers of fast internet access on employment and wages. Similarly, Abreha et al. (2021) document increases in firm-level productivity, wages, and employment following expanded mobile internet access. These findings suggest that digital infrastructure operates as a complementary input that raises aggregate labor demand and can generate broad-based wage gains, even in contexts where worker-level digital skills are limited.

However, the wage returns from digital *skills*, distinct from access to digital infrastructure, are primarily realized through occupational sorting into skill-intensive positions, a mechanism that is more restricted in labor markets with limited formal sector employment opportunities, as is characteristic of Indonesia (Falck et al., 2021). On the other hand, study from Ganju et al., (2021) showed that basic IT skills significantly increase employment probability, with effects operating through both higher labor force participation and a greater likelihood of transitioning from unemployment to formal employment. Research specifically examining Indonesia's experience with digitalization and labor market outcomes is more limited but growing.

Study from Kustanto (2024) examines whether ICT diffusion reduces income inequality, finding that while digital development is associated with economic growth, its distributional effects are heterogeneous and depend on the existing infrastructure and human capital base of provinces. Next, Kis-Katos et al., (2014) find that skill-biased demand shifts consistent with technological change propagated through imported intermediate inputs and FDI in the manufacturing sector.

METHODOLOGY

This study employs a quantitative approach using cross-sectional econometric analysis to identify the presence of a digital skill premium in the Indonesian labor market. The data are derived from the 2024 wave of the National Labor Force Survey (SAKERNAS) conducted by Statistics Indonesia (BPS). The unit of analysis consists of

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individuals of productive age (15–64 years) who are employed either full-time or part-time and receive wages in Indonesia. The dataset includes information on demographic characteristics, education, employment, and income.

The variables used in this study comprise the dependent variable, independent (treatment) variables, and control variables. The dependent variable is monthly wages, transformed into natural logarithmic form (ln_wage) to address right-skewed distribution and to enable percentage-based interpretation of coefficients. The independent variable is digital skills utilized in the workplace. The proxies include: (1) a dummy variable indicating the use of computers/mobile phones/other digital technologies in work; (2) a dummy variable indicating access to internet use in work; and (3) occupational categories classified as "digital-intensive" based on ISCO-08 codes (ILO, 2012). Meanwhile, the control variables consist of demographic characteristics (gender, marital status, domicile, generational category), education, work experience, and occupational categories.

Table 1. Definition of Operational Variables

Variable	Definition	Measurement Scale
Ln_wage	Natural logarithm of wages (How much net income/earnings/salary/wage did (NAME) receive during the last month from this main job or main business activity? (Included in salary/wage: performance assessment, position assessment/functional assessment/certification assessment, cost of living assessment/high cost assessment).	Ratio
Internet	In the last month, has (NAME) used the internet (including using Whatsapp, Facebook, Instagram, X/Twitter, and other social media)	Nominal 1 : using internet 0 : not using internet
Tec_digital	In the last month, has (NAME) used the internet (Computer/Mobile phone/Smartphone/Other digital technology)	Nominal 1 : Using digital technology 0 : Not using digital technology
Digital-intensive	Jobs that routinely use computers, software, or digital skills are integrated based on the ISCO-08 grouping.	Nominal 1 : Digital Intensive

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		Occupation (ISCO-08 group 1 – 4) 0 : Non-digital occupations (ISCO-08 group 5-9)
Work_exp	First year of employment - current year (survey wave period)	Ratio
Formal	What is (NAME)'s primary employment status? Formal sector indicators: Self-employed, self-employed with temporary assistance, self-employed with permanent assistance and paid, worker/employee/staff registered in the licensing system.	Nominal 1 : Formal sector 0 : Non Formal sector
Agri_sec	In the past week, in what field was (NAME)'s main job?	Nominal 1 : Agriculture 0 : Non agriculture
Skill_job	Occupational categories classified according to ISCO-08. Category 3: Managers, Professionals, Technicians, and Associate Professionals Category 2: Administrative Support Workers; Service and Sales Workers; Skilled Agricultural, Forestry, and Fisheries Workers; Craft and Related Trade Workers; Machine and Plant Operators and Assemblers Category 1: Basic Occupations, plant and machine operators and assemblers, and basic occupations	Nominal 1 : Low-Skilled Job 2 : Middle-skilled Job 3 : High-skilled Job
Ln_Workhours	How many hours do you typically work per week at this main job?	Ratio
Educ	Length of formal education completed (years)	Ratio
Gender	Respondent gender	Nominal 1 : Men 0 : Women
Marital Status	Respondent's marital status	Nominal

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		1 : Never or ever married 0 : Married
Generation	Respondents' age generation category Gen Baby boomer: 1946 - 1964 (>60) Gen X : 1965 - 1980 (44-59) Gen Milenial : 1981 - 1996 (28 - 43) Gen Z : 1997 - 2012 (12 - 27)	Nominal 1 : Baby boomer 2 : Gen X 3 : Gen Millenial 4 : Gen Z

Source: SAKERNAS data, 2024

The basic model of this research refers to the Mincer wage function (1974), which explains the relationship between education level, work experience, and income. The general form of the Mincer function can be expressed as follows:

$$Wage_i = e^{(\beta_0 + \beta_1 S_i + \beta_2 Exp_i + \beta_3 Exp_i^2 + \mu_0} \quad \text{.....(1)}$$

Where W_i is the income of individual i, S_i represents the length of formal education, and Exp_i represents work experience. Taking the natural logarithm of both sides, the function is transformed into a linear model:

$$\ln(Wage_i) = \beta_0 + \beta_1 S_i + \beta_2 Exp_i + \beta_3 Exp_i^2 + \mu_0 \quad \text{.....(2)}$$

To align with the research focus on workforce digitalization, the Mincer model was then modified by adding variables representing digital skills, gender, and their interaction, so that the complete model is written as:

$$\ln(Wage_i) = \beta_0 + \sum \beta_n Digital_{in} + \sum \beta_n X_{in} + \varepsilon_i \quad \text{.....(3)}$$

In this model, $\ln(Wage_i)$ represents the natural logarithm of the wage of individual i. The variable $Digital_i$is a dummy variable that takes the value of 1 if an individual is employed in an occupation classified as digital-intensive, and 0 otherwise. Meanwhile, X_i denotes a vector of control variables that includes other factors potentially affecting wages, such as demographic characteristics, level of education, work experience, employment status (formal or informal), agricultural or non-agricultural sector, occupational category, working hours, and generational category. The component ϵ_i represents the error term, capturing the influence of other factors outside the model. The model is estimated using Ordinary Least Squares (OLS) regression with robust standard errors to address potential heteroskedasticity in cross-sectional data (Patrinos, 2024). This approach provides a more intuitive and visual interpretation of the interaction coefficients generated by the OLS model (Wooldridge, 2016).

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RESULT AND DISCUSSION

Result

The descriptive statistics presented in Table 2 provide an overview of the characteristics of workers included in this study. The average monthly net wage of workers in Indonesia is recorded at IDR 2,603,725, with a standard deviation of IDR 3,454,210, indicating substantial wage variation across individuals. The minimum value of IDR 300,000 and the maximum reaching IDR 100 million suggest a considerable level of income inequality in the labor market. In terms of digitalization, approximately 44.3 percent of workers use the internet in their jobs, while 57.1 percent report using digital technologies at work. In addition, around 54.7 percent of workers are employed in occupations that routinely require digital skills, based on the ISCO-08 classification.

Table 2. Description of Data Frequency

Variable	Mean	Std. Deviasi	Min	Max
Monthly wages	2,603,725	3,454,210	300,000	1,00e+08
Internet Use at Work	0.443	0.496	0	1
Digital Technology Use at Work	0.571	0.494	0	1
Occupational Groups That Regularly use digital skills (ISCO-08)	0.547	0.227	0	1
Occupational Skill Level Categories based on ISCO-08	1.948	0.395	1	3
Occupational Sector (Agriculture)	0.421	0.494	0	1
Work Experience	12.699	11.441	0	59
Occupational Type	0.044	0.205	0	1
Working hours	40.12	18.88	1	98
Years of education	8.137	4.441	0	22
Generation category	2.379	0.758	1	4
Gender	0643	0.479	0	1

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Western Indonesia region category	0.648	0.477	0	1
Marital status	0.183	0.387	0	1
Total of observation	177,182			

Source: SAKERNAS data was processed by author, 2025

Furthermore, 42.1 percent of workers are employed in the agricultural sector, while the remainder are distributed across the industrial and service sectors. The average work experience is 12.7 years, with a standard deviation of 11.4 years, indicating a relatively heterogeneous distribution of work experience among individuals. The average weekly working hours amount to 40.1 hours, consistent with formal labor standards, and the average years of schooling reach 8.1 years, equivalent to a junior secondary education level. The proportion of male workers is 64.3 percent, reflecting a male-dominated labor force structure. From a regional perspective, approximately 64.8 percent of workers are from Western Indonesia, while the rest are located in Eastern Indonesia. In terms of marital status, 18.3 percent of workers are reported to be married.

Overall, these results indicate that Indonesia's labor force is still predominantly composed of individuals with a moderate level of education, with an increasing level of digitalization and a relatively balanced distribution between the western and eastern regions. However, the substantial variation observed in wages, work experience, and working hours suggests the presence of persistent inequalities in the national labor market.

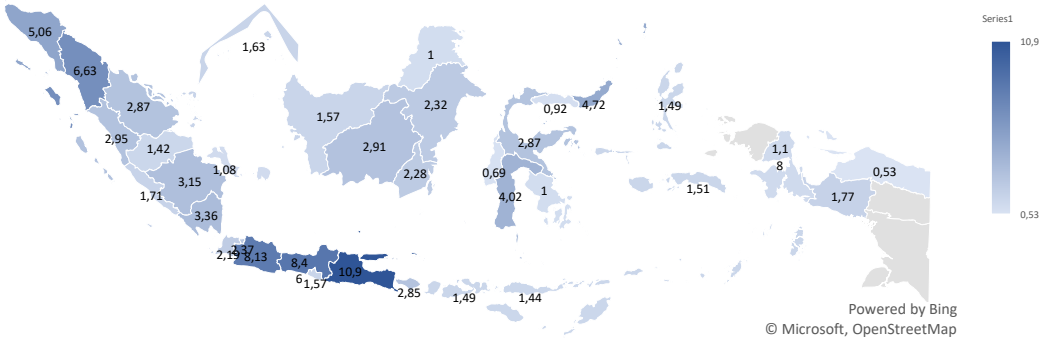


Figure 1. Map Of The Distribution Of Digital-Intensive Jobs By Region In Indonesia In 2024.
Source: SAKERNAS data was processed by the author, 2025

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Figure 1 illustrates the spatial distribution of the proportion of workers engaged in digital-intensive occupations in Indonesia in 2024. It shows that digital-based employment remains concentrated in the western part of Indonesia, particularly on the islands of Java and Bali. The Province of DKI Jakarta records the highest percentage of digital-intensive workers at 10.9 percent, followed by DI Yogyakarta (8.46 percent) and West Java (8.13 percent). This indicates that regions with higher economic concentration and better digital infrastructure tend to have a greater share of digital labor.

In contrast, regions in Eastern Indonesia exhibit relatively low proportions of digital-intensive workers. For instance, Papua and Maluku record only around 0.53 percent and 1.1 percent, respectively, while Sulawesi and Nusa Tenggara range between 1.4–2.8 percent. This disparity reflects a significant regional digital divide, both in terms of technology adoption and human capital capacity. In general, this map confirms that digital transformation in Indonesia's labor market remains concentrated in the western region, particularly in provinces with higher levels of urbanization and more advanced economic infrastructure. These findings reinforce the argument that digital development policies should be directed toward expanding access to and improving digital skills in eastern regions, in order to support more inclusive and equitable economic growth across all parts of Indonesia.

Table 3. Multicollinearity Test

Variables	VIF	1/VIF
Internet use at work	2.60	0.3846
Use of digital technology at work	2.48	0.4038
Occupational groups that regularly use digital skills (ISCO-08)	1.88	0.5305
Occupational skill level categories based on ISCO-08	1.84	0.5427
Occupational sector (agriculture)	1.60	0.6265
Work experience	1.29	0.7742
Type of occupation	1.08	0.9288
Working hours	1.10	0.9060
Years of education	1.29	0.7734
Generation categories	1.30	0.7690
Gender	1.25	0.7983

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Region	1.07	0.9374
Marital status	1.05	0.9555
Mean VIF	**1.53**	

Source: SAKERNAS data was processed by the author, 2025

The results of the multicollinearity test presented in Table 3 indicate that all independent variables in the regression model have Variance Inflation Factor (VIF) values well below the common threshold of 10, with a mean VIF of 1.53. This suggests that there is no serious multicollinearity problem among the explanatory variables in the model.

Furthermore, the 1/VIF values, ranging from 0.3846 to 0.9555, reinforce the conclusion that the linear relationships among the independent variables do not distort the estimation of the regression coefficients. Each variable in the model provides unique and non-redundant information in explaining the variation in workers' wages. Thus, the regression model used in this study can be considered to satisfy the assumption of no multicollinearity, ensuring that the estimation results can be interpreted in a valid and reliable manner.

The estimation results presented in Table 4 show that digital skills have a strong and significant effect on increasing workers' wages in Indonesia. Workers who use the internet in their jobs earn approximately 14.8 percent higher income compared to those who do not. Meanwhile, the direct use of digital technologies in the workplace yields an even larger wage premium, at around 20.7 percent. The most pronounced effect is observed among workers in digital-intensive occupations, where wages are approximately 37.5 percent higher than those of workers in non-digital sectors. These findings confirm the existence of a substantial digital skill premium in Indonesia's labor market.

In addition to digital skills, other factors such as education and work experience also play important roles. Each additional year of schooling increases average wages by about 1.8 percent, while each additional year of work experience raises earnings by approximately 0.3 percent. From a demographic perspective, male workers have a significant wage advantage of about 42.9 percent compared to female workers, indicating a persistent gender gap in the labor market, including in digital-related occupations. Marital status also shows a negative effect on wages, where workers who are unmarried or previously married earn less than those who are married.

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Table 4. Multiple Regression Result

Independent variables	**Model 1: Determinant of Digital Wage**
JOB_INTERNET (Internet use at work = 1. Ya)	**0.148*** (0.005)**
JOB_DIGITAL (Use of digital technology at work = 1. Ya)	**0.207*** (0.005)**
DIGITAL_INTENSIVE (Occupational routine use of digital skills (ISCO-08) = 1. Digital Intensive)	**0.375*** (0.078)**
Control Variables	
EDUC (Years of education)	**0.018*** (0.0004)**
WORK_EXPERIENCE	**0.003*** (0.0002)**
GENDER Respondent's gender = 1. Men	**0.429*** (0.004)**
Marital status 1 = Never / ever married	**-0.052*** (0.005)**
GENERATION (*base : Gen Babyboomer*) Age Generation Category = 2. Gen X Age Generation Category = 3. Gen Millenial Age Generation Category = 4. Gen Z	 **0.071*** (0.006)** 0.017 (0.006) **-0.175*** (0.009**)
SKILL_JOB (*base : Low-skilled occupation*)	
Middle-skilled Occupation	**0.109*** (0.005)**
High-skilled Occupation	0.022 (0.078)
WORKING_HOURS Logarithm of working hours	**0.236*** (0.004)**
AGRICULTURE Type of Occupation = 1. Agriculture	**-0.121*** (0.004)**
FORMAL	**0.532***

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Work status = 1. Formal sector	**(0.010)**
REGION 1 = Western Indonesia	**0.046***** **(0.004)**
Constanta	**12.768***** **(0.015)**
Observations	171,182
Prob > F	0.0000*** *
R-squared	0.2409

Note: Robust standard errors in parentheses: *** p<0.001, ** p<0.01, * p<0.05
Source: SAKERNAS data was processed by the author, 2025

Across generational groups, Generation X earns the highest wage premium, approximately 7.1 percent higher than the Baby Boomer cohort as the reference group. In contrast, Generation Z earns about 17.5 percent lower wages compared to the base category, while the results for Millennials are not statistically significant. This pattern suggests that although younger generations tend to be more familiar with digital technologies, this advantage has not yet fully translated into higher earnings.

In terms of occupational categories, workers in middle-skilled occupations earn around 10.9 percent higher wages compared to those in low-skilled occupations (the reference group). Although the coefficient for high-skilled occupations is not statistically significant, this may indicate that in the Indonesian context, high-skilled jobs that are not necessarily digital-based do not always provide wage compensation commensurate with the level of skills possessed.

Furthermore, working hours exhibit a positive and significant relationship with wages. The coefficient of 0.236 indicates that an increase in weekly working hours is associated with higher income, suggesting that productivity and work intensity remain key determinants of wage setting in Indonesia's labor market. On the other hand, workers in the agricultural sector earn approximately 12.1 percent lower wages compared to those in the non-agricultural sector. This reflects the lower value-added of the agricultural sector as well as the limited adoption of digital technologies in its production activities. Workers in the formal sector receive, on average, 53.2 percent higher wages than those in the informal sector. This finding reinforces evidence of a formal wage premium in Indonesia, where the formal sector not only provides job stability but is also more open to the adoption of digital technologies and knowledge-based skills.

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From a geographical perspective, the results indicate that workers in Western Indonesia earn 4.6 percent higher wages than those in Eastern Indonesia. This suggests that digitalization and technology-based economic activities remain concentrated in the western region. Furthermore, the coefficient of determination (R-squared) of 0.2409 indicates that the model explains approximately 24 percent of the variation in workers' wages in Indonesia. Digital factors, demographics, education, and job characteristics jointly contribute significantly to income variation in the national labor market. This value is reasonably strong for a large-scale cross-sectional model such as SAKERNAS data.

The R^2 value of 0.2409 further implies that around 24 percent of wage variation can be explained by demographic characteristics, education, experience, and digital skills, while the remaining variation is influenced by other factors outside the model. The Prob > F value of 0.0000 indicates that all independent variables are jointly significant in affecting wage levels, suggesting that the model is well-fitted and appropriate for further interpretation.

DISCUSSION

At this point, the discussion is presented in a detailed and comprehensive manner based on the previous regression results. The estimation results indicate that workers who use the internet and digital technologies earn significantly higher wages compared to those who do not. These findings confirm the existence of a digital skill premium in Indonesia's labor market. This phenomenon is consistent with the concept of a digital skill premium, defined as additional compensation received by workers who possess information and communication technology (ICT)-based skills. According to the theory of skill-biased technological change (SBTC) developed by Autor et al. (2003), technological advancement increases the demand for workers with non-routine, analytical, and digital skills, while reducing the demand for routine and manual jobs. In this context, technology functions not only as a production tool but also as a mechanism for skill selection that enhances the relative productivity of workers who can adapt to digital technologies.

The wage increase of approximately 14–22 percent for workers who use the internet and digital technologies in their jobs highlights that digital capability not only improves individual productivity but also strengthens workers' bargaining power in the labor market. Empirical evidence from both developing and developed countries supports this finding. For instance, studies such as Oliver Falck et al. (2021) in Europe and Alekseeva et al. (2021) in the United States show that the ability to use digital tools and data-driven systems increases the returns to human capital. Similarly, research by Liu et

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al. (2024) in China finds that digital literacy enhances workers' likelihood of obtaining formal employment and higher wages. Thus, the results of this study confirm that the global trend of rising wages driven by digital skills is also evident in Indonesia, albeit within a different structural context.

However, from a structural perspective, it is important to note that Indonesia's labor market is still undergoing a digital transition that is not yet evenly distributed. This is reflected in the descriptive statistics, which show that only about 44.3 percent of workers use the internet in their jobs, and 57.1 percent use digital technologies. These figures indicate that the penetration of digital skills in the labor market remains limited, particularly outside the service sector and the formal industrial sector. In a situation where the supply of digital skills is relatively low while demand is increasing rapidly, an excess demand for digital skills emerges, leading to a positive wage premium for digitally skilled workers.

This wage premium can also be explained through the mechanism of complementarity between technology and human capital, as discussed by Carlos Correa et al. (2017). Digital technology enhances productivity for individuals who already possess strong cognitive and analytical skills, enabling them to utilize tools and information more efficiently. In the context of a modified Mincer wage function, digital skills act as a reinforcing factor that amplifies the returns to education, meaning that education and digital skills complement and strengthen each other. Highly educated workers who master digital technologies obtain a double premium, benefiting both from formal education and additional compensation due to their digital competencies. Firms tend to offer higher wages to workers with demonstrated digital capacity, as they are perceived to be more efficient, easier to train, and capable of operating across technology-based systems.

These findings also indicate the presence of skill polarization in Indonesia, where occupations requiring high levels of digital skills (such as managerial, professional, and technical roles) receive substantial wage premiums, while middle-skilled jobs do not experience comparable wage growth. This pattern is consistent with studies by Arntz et al. (2019) and Daron Acemoglu & Restrepo (2020), which explain that digitalization tends to reshape the job structure toward two extremes, high-skill digital jobs and low-skill manual jobs, while middle-skilled occupations are more vulnerable to disruption. In the Indonesian context, this is reflected in the large proportion of workers with moderate education levels who have not yet fully benefited from digitalization.

From a regional perspective, the distribution map shows a concentration of digital-intensive jobs in urban areas, particularly in Java and Bali. Regions with stronger digital infrastructure and more developed formal economies exhibit larger digital wage

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premiums. This condition aligns with the urban productivity premium theory proposed by Matano & Naticchioni (2016), which suggests that economic agglomeration in large cities creates greater opportunities for interaction between human capital and technology, resulting in higher productivity and wages. In contrast, workers in rural areas and Eastern Indonesia remain relatively disadvantaged due to limited access to technology, training, and digital infrastructure.

In conclusion, this study highlights two important realities in Indonesia's labor market. First, digital skills provide tangible economic value, not only in terms of employment opportunities but also through direct wage increases. Second, the benefits of digitalization are not yet evenly distributed across sectors and regions. Without targeted policy interventions, the digital skill premium may widen economic inequality and reinforce labor market segmentation. The existence of a digital skill premium in Indonesia thus reflects both progress and challenge. On one hand, it demonstrates the effectiveness of technology adoption in enhancing productivity and worker welfare; on the other hand, it underscores the need for inclusive strategies to ensure that the digital economy generates not only growth, but also economic and social equity in the era of digital transformation.

CONCLUSION

This study provides strong empirical evidence that digital skills play a significant role in determining wage levels in Indonesia's labor market. The estimation results using microdata from SAKERNAS 2024 indicate the presence of a clear and consistent digital skill premium across all models and income distributions. Workers who use the internet, digital technologies, or are employed in digital-intensive occupations earn higher wages compared to those who do not possess such skills. These findings confirm that digitalization has created structural changes in the Indonesian labor market that favor individuals with digital competencies. The recommendations of this study emphasize the importance of upskilling and reskilling strategies to broaden the economic benefits of digital transformation. The government needs to strengthen vocational education programs and technology-based training that are inclusive, particularly for women, young workers, and communities in Eastern Indonesia. In addition, strengthening an equitable digital ecosystem will be key to ensuring that digital transformation does not only create digital winners, but also provides equal opportunities for all segments of the workforce.

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REFERENCES

Abreha, K., Choi, J., Kassa, W., Kim, H. J., & Kugler, M. (2021). Mobile access expansion and price information diffusion: Firm performance after Ethiopia's transition to 3G in 2008. World Bank Policy Research Working Paper No. 9752.

Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In O. Ashenfelter & D. Card (Eds.), Handbook of Labor Economics (Vol. 4B, pp. 1043–1171). Elsevier.

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from us labor markets. *Journal of Political Economy*, *128*(6), 2188–2244. https://doi.org/10.1086/705716

Alekseeva, L., Azar, J., Giné, M., Samila, S., & Taska, B. (2021). The demand for AI skills in the labor market. *Labour Economics*, *71*, 1–60. https://doi.org/10.1016/j.labeco.2021.102002

Arntz, I. Z. A. D. P., Arntz, M., Zierahn, U., Arntz, M., & Zierahn, U. (2019). *DISCUSSION PAPER SERIES Digitalization and the Future of Work : Macroeconomic Consequences Digitalization and the Future of Work : Macroeconomic Consequences*. *12428*

Asian Development Bank. (2014). Technological change, skill demand, and wage inequality in Indonesia. ADB Working Paper Series. Asian Development Bank.

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics*, Vol.*118*(4), pp.1279–1333.

Becker, G. S. (1962). Investment in human capital: A theoretical analysis. Journal of Political Economy, 70(5, Part 2), 9–49

Berman, E., Somanathan, R., & Tan, H. W. (2005). Is skill-biased technological change here yet? Evidence from Indian manufacturing in the 1990s. World Bank Policy Research Working Paper No. 3761.

Chen, Z., Ge, Y., & Lai, H. (2010). Foreign direct investment and wage inequality: Evidence from China. World Development, 39(8), 1322–1332.

Correa, Juan A., Lorca, Miguel., Parro, F. (2017). Capital–Skill Complementarity: Does Capital Composition Matter? *The Scandinavian Journal of Economics*, *121*(1), 89–116. https://doi.org/10.1111/sjoe.12267

Deming, D. J. (2022). Four facts about human capital. Journal of Economic Perspectives, 36(3), 75–102.

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

Federal Reserve Bank of Atlanta. (2023). Closing the digital skill divide. National Skills Coalition & Federal Reserve Bank of Atlanta. Retrieved from https://www.atlantafed.org

Falck, O., Heimisch-Roecker, A., & Wiederhold, S. (2021). Returns to ICT skills. *Research Policy*, *50*(7), 104064. https://doi.org/10.1016/j.respol.2020.104064

Ganju, K. L., Pavlou, P. A., & Raghu, T. S. (2021). IT skills, labor market outcomes, and employment transitions: Evidence from an emerging economy. Information Systems Research, 32(3), 952–970.

Garcia-Lazaro, A., Mendez-Astudillo, J., Lattanzio, S., Larkin, C., & Newnes, L. (2025). The digital skill premium: Evidence from job vacancy data. Economics Letters, 250, 112294.

Hanushek, E. A. (2013). Economic growth in developing countries: The role of human capital. Economics of Education Review, 37, 204–212.

Hidayat, L., & Kadir, K. (2025). Semantic network analysis of digital marketing labor demand in Indonesia. Jurnal Ketenagakerjaan. Ministry of Manpower of the Republic of Indonesia.

Hjort, J., & Poulsen, J. (2019). The arrival of fast internet and employment in Africa. American Economic Review, 109(3), 1032–1079.

Kis-Katos, K., Pieters, J., & Sparrow, R. (2014). Technological change, skill demand, and wage inequality: Evidence from Indonesia. World Development, 57, 93–104.

Kustanto, A. (2024). Can ICT diffusion reduce income inequality for a better life? Evidence from Indonesian provinces. Asian Journal of Applied Economics, 31(1), 1–36.

Liu, Che-Wei., Saldanha, Terence J.V., Mithas, S. (2024). Can Digital Skills Empower Disadvantaged Castes and Women? Evidence From India. *Production and Operations Management*, *34*(4), 760–776. https://doi.org/10.1177/10591478241248749

Lu, W., & Yuan, W. (2024). Digital service trade and the wage income gap between urban and rural residents: Empirical evidence from China. SAGE Open, 14(1).

Matano, A., & Naticchioni, P. (2016). What drives the urban wage premium? Evidence along the wage distribution. *Journal of Regional Science*, *56*(2), 191–209. https://doi.org/10.1111/jors.12235

Mincer, J. (1974). Schooling, experience, and earnings. Columbia University Press.

Nogueira, M. C., & Madaleno, M. (2023). New evidence about skill-biased technological change and gender wage inequality. Economies, 11(7), 193.

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

OECD. (2025). OECD skills outlook 2025: From skills to labour market opportunities. OECD Publishing. https://doi.org/10.1787/26163cd3-en

Patrinos, H. (2024). Estimating the return to schooling using the Mincer equation. *IZA World of Labor*. https://doi.org/10.15185/izawol.278.v2

Psacharopoulos, G., & Patrinos, H. A. (2018). Returns to investment in education: A decennial review of the global literature. Education Economics, 26(5), 445–458.

Robert Half. (2026). 2026 salary guide. Robert Half International. Retrieved from https://www.roberthalf.com

Santoso, D., Rahmawati, F., Murniati, M., & Sukoco, I. (2023). The Indonesian digital workforce gaps in 2021–2025. Sustainability, 15(1), 754. https://doi.org/10.3390/su15010754

Wooldridge, J. M. 6th E. (2016). *Introductory Econometrics: A Modern Approach* (6th Editio). Cengage Learning.

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