Vol. 19 No.2. Agustus 2026 ISSN : 2301-8968

JURNAL EKONOMI KUANTITATIF TERAPAN

JEKT	Volume 19	Nomor 2	Halaman 235-437	Denpasar Agustus 2026	ISSN 2301-8968

pISSN : 2301 – 8968
JEKT ♦ 19 [2] : 401-416 eISSN : 2303 – 0186

When Education Does Not Fit the Job Pathways to Employment in Digital Sectors

ABSTRACT

This study examines job-education mismatch in Indonesia's high-digital-intensity (HDI) sectors, focusing on vertical mismatch in the form of overeducation and undereducation. Using data from the 2018 National Labor Force Survey (Sakernas) and applying a logit model, the research assesses the probability of highly educated individuals with mismatched qualifications entering the SID sector. The findings show that overqualified workers experience an 18.4% lower likelihood of joining SID compared to well-matched individuals, while underqualified workers face a 6.10% penalty. Overqualification leads to skill underutilization and reduced job satisfaction, whereas underqualified workers may still enter operational digital roles. Additionally, demographic characteristics gender, age, urban residence, and internet usage—significantly affect SID participation, with men, younger individuals, urban residents, and active internet users showing higher probabilities. The study highlights the need for adaptive education systems, stronger digital skills, and policies that align workforce capabilities with the rapidly evolving demands of Indonesia's digital economy.

Keywords: job mismatch, wage penalty, logit, high digital intensity sector
JEL Classification Codes: J24, J31, C25, O33.

INTRODUCTION

In Indonesia, there is a significant prevalence of job-education mismatch, where workers' educational levels do not align with job requirements. Based on the Sakernas (2018) data, nearly half of the workforce has higher education levels than their jobs demand. This phenomenon contributes to the low performance of Indonesia's human capital index in terms of know-how. Although educational expansion over the past two decades has produced a more qualified workforce, limited job creation for individuals with intermediate to high skills has exacerbated the mismatch issue *(Das et al., 2016; Salas-Velasco, 2021)*. This situation is further aggravated by the impact of computer and internet technologies, which have transformed over 800 occupations, 2,000 job types, and 18 required skills globally *(Calvino et al., 2018)*. In Indonesia, technology has altered the nature of work since 2000, with machines eliminating approximately 5.5 hours of repetitive and manual tasks from the average weekly workload *(Prospera, 2019)*. Therefore, it is crucial to examine the alignment between education and employment amid technological advancements.

Educational mismatch can have various negative impacts on individuals, such as job dissatisfaction, decreased skills due to limited access to further education and training, low labor productivity, suboptimal labor utilization, and wage penalties *(Allen & Van der Velden, 2001; Büchel & Mertens, 2004; Quintini, 2011; Tsang & Levin, 1985)*. This phenomenon can also contribute to low productivity in the economic sector and even economic growth without job creation (jobless growth). Structural mismatches in the labor market can cause unemployment and hinder investment and job growth. Developing countries, such as Indonesia, have specific labor market characteristics that can influence the relationship between educational mismatch and income. Indonesia is classified as a middle-income country by the World Bank and has an emerging market and developing economy. Analyzing educational mismatches and their impact on earnings in the Indonesian labor market is interesting to study, given the various economic and social factors that influence employment conditions in the country.

Indonesia's higher education sector has undergone significant structural changes over the past two decades. Recent data shows that, overall, the average number of college graduates in Indonesia has reached 17.93 percent of the population aged 25-34. However, along with the expansion of higher education, a paradox has emerged regarding college graduate unemployment. The unemployment rate for educated individuals (higher education and diploma graduates) increased from 4.54% and 5.03% in 2016 to 5.25% and 4.83% in 2024.

In general, there is agreement that job-education mismatch can have a negative impact on productivity. Empirical evidence suggests that placing workers in positions that require lower educational qualifications than they possess is potentially counterproductive *(Tsang & Levin, 1985)*, as it can lead to suboptimal utilization of skills and reduced productivity *(Yeo & Maani, 2017)*. Similarly, if individuals work in positions that require higher qualifications than they possess, this can also result in low productivity. One factor contributing to low productivity levels in Indonesia is likely the skills imbalance in the labor market, where workers' skills do not match the needs of available jobs.

On the other hand, much research in the field of educational economics has focused on the incidence of job mismatch and its impact on earnings. Most of these studies have been conducted only in developed countries, especially in North America and Europe (members of the OECD), due to the availability of comprehensive databases for analysis, such as the Programme for International Assessment of Adult Competencies (PIAAC) *(Levels, Van der Velden & Di Stasio, 2014; Montt, 2017)*. Other findings indicate that reducing the level of job mismatch will have a positive impact on increasing output per capita *(Abdulla, 2024)*. Furthermore, it occurs in Asia, especially Japan, which shows that horizontal education-job mismatch has the potential for significant economic, organizational, and individual costs *(Hirao, 2024)*. To narrow the research gap, this study aims to provide empirical evidence from Indonesia as a developing country regarding two types of job mismatch: vertical mismatch, which compares the number of years of education required for a job with the actual number of years of education of workers, and horizontal mismatch, which compares the educational major required for a job with the educational major taken by workers. Specifically, this research will focus on analyzing the tendency of higher education graduates with vertical mismatch to work in high digital intensity (HDI) sectors.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Human capital investmen theory

The theory of human capital investment explains that education, training, and work experience are forms of investment made by individuals to increase productivity and future income *(Becker, 1964; Mincer, 1974)*. Through formal education and training, individuals acquire skills and knowledge that improve their contribution to the production process. Within this framework, the costs incurred to obtain education—whether in the form of time, money, or opportunity—is considered an investment that will provide a return in the form of increased income.

The most common model explaining this relationship is the Mincer earnings function, which shows that each additional year of education increases a person's wages, albeit with diminishing returns. Therefore, the higher a person's education and work experience, the greater their potential earnings. However, the returns from this investment depend heavily on the labor market's ability to absorb workers with those qualifications. When there is a mismatch between educational qualifications and the types of jobs available—as in the case of a vertical mismatch—investment in education is suboptimal and can lead to a wage penalty for workers who are overqualified but work in an unsuitable sector with their abilities.

Vertical Mismatch

Vertical mismatch refers to a situation where a worker's education level does not match the educational requirements of their job, either in the form of overeducation or undereducation. This phenomenon has been widely studied in labor economics literature because it has direct implications for labor market efficiency, productivity, and wage structures. The mismatch between a worker's education level and the educational requirements of their job often results in a wage penalty for overeducated workers, as they are unable to maximize the returns on their human capital *(Hartog, 2000)*.

The following is the identification of vertical mismatch in this study based on the table below:

Figure 1: Vertikal mismatch Identification

	Type of Occupation	Primary education level	Secondary education level	First stage of tertiary education	Second stage of tertiary education
		Up to Elementary school	Junior and Senior High School	Diploma I/II	Diploma III to Doctoral
1	Managers	U	U	M	O
2	Professionals	U	U	U	M
3	Technicians and Associate Professionals	U	U	M	O
4	Clerical Support Workers	U	M	O	O
5	Services and Sales Workers	U	M	O	O
6	Skilled Agricultural, Forestry and Fishery Workers	U	M	O	O
7	Craft and Related Trade Workers	U	M	O	O
8	Plant and Machine Operators and Assemblers	U	M	O	O
9	Elementary Occupations	M	O	O	O

Note: U stands for "Underqualified", M stands for "Well-matched", and O stands of "Overqualified"

Research shows that vertical mismatch can reduce job satisfaction and overall organizational performance (*Allen & Van der Velden, 2001*). Meanwhile, other opinions emphasize the importance of distinguishing between real and apparent mismatch, because some workers may still have suitable skills even though they appear to be formally mismatched (*McGuinness & Sloane, 2011*).

In developing countries, mismatch is more complex because there is often a mismatch between educational expansion and structural transformation of the economy, as is also seen in Indonesia (*Suryadarma et al., 2006*).

In the context of the digital economy sector, vertical mismatch exhibits different dynamics. Formal educational qualifications are not always the primary indicator of competence in the fast- evolving digital sector, which relies heavily on technical and informal skills such as coding, data analysis, and digital communication. Literature shows that many digital occupations place greater value on digital literacy than on formal academic degrees *(OECD, 2020)*. As a result, many higher education graduates in Indonesia experience mismatch in the digital sector because university curricula have not fully adjusted to the skill demands of Industry 4.0, thereby increasing the risk of wage penalties even within rapidly expanding sectors.

High Digital Intensity Sector

The digital intensity categorization in this study is based on Calvino. This concept examines differences in the development and adoption of new technologies across sectors using seven indicators: software investment, investment in tangible ICT assets, intermediate ICT goods, intermediate ICT services, robot use, revenue from online sales, and human resources with ICT specialization. When compared with other digital intensity categorizations, such as Comin (2013), Spieza (2011), Colecchia (2002), and McKinsey (2015), Calvino's digital intensity categorization is the most comprehensive.

Seven indicator matrices are used to categorize sectors based on their level of digital intensity, as developed in the OECD's digital-intensity taxonomy *(Calvino et al., 2018)*. The indicators considered include:

1. Software Investment
2. Investment in Tangible ICT Assets
3. Intermediate ICT Goods
4. ICT Intermediate Service
5. Use of Robots
6. Income from online sales

7. Human resources with ICT specialization

Determining whether a sector falls into the low, medium, and high digital intensity categories in this study follows the following procedure:

a. The value of each SID determining indicator is grouped based on the quartile of the value. The sector is then assigned a code or value equal to its quartile level and weighted by the total number of sectors in the global taxonomy, which is 36. To illustrate, for example, the agricultural sector's software investment value falls within the lowest quartile compared to other sectors. Therefore, the agricultural sector has a value of 1/36, or 0.028, for this indicator.
b. The weighted values of each indicator are then averaged to determine the digital intensity score. If the average intensity value for a sector is below the median of all sector scores (36), then the sector falls into the low digital intensity category. Conversely, if the intensity value for the sector is above the median, then the sector falls into the high SID category. Meanwhile, if the intensity value is at the median, the sector falls into the medium SID category.

Sector grouping based on digital intensity levels cannot be used as a tool to measure the digital economy, but rather as a proxy for digital transformation within a sector. This measure is intended as an operational tool to help policymakers better understand and monitor ongoing digital transformation at the industry level, allowing them to focus on R&D spending, the ICT industry, human resource development, and corporate innovation activities.

Table 1: Digital Intensity Sector Taxonomy: Global Indicators

No	Sector	ISIC Rev 4.	Digital Intensity
1	Agriculture, Forestry, and Fisheries	01-03	Low
2	Mining and Quarrying	05-09	Low
3	Food, Beverage, and Processed Products Tobacco	10-12	Low
4	Textiles, Apparel, and Leather	13-15	Medium- Low
5	Wood, Paper, and Printing	16-18	Medium- High
6	Coal Products and Petroleum Refinery	19	Medium- Low
7	Chemical Products and Chemical Products	20	Medium- Low
8	Pharmaceutical Products	21	Medium- Low
9	Rubber and Plastic Production	22-23	Medium- Low
10	Base Metals and Metal Goods	24-25	Medium- Low
11	Computers, Electronics, and Optics	26	Medium- High
12	Electrical Equipment	27	Medium- High
13	Machinery and Equipment Ytdl	28	Medium- High
14	Transportation and Means of Transport	29-30	High
15	Furniture, Other Processing, Machine Repair	31-33	Medium- High
16	Supply of Electricity, Steam, and Cold Air	35	Low
17	Water, Wastewater, and Waste Management	36-39	Low
18	Construction	41-43	Low
19	Wholesale, Retail, and Repair Trade	45-47	Medium- High
20	Transportation and Warehousing	49-53	Low
21	Accommodation and Activities Food, and Drink Providers	55-56	Low
22	Publishing Activities, Audio Visual, and Broadcasting	58-60	Medium- High
23	Telecommunications	61	High
24	IT and Information Services Activities	62-63	High
25	Finance and Insurance	64-66	High
26	Real Estate	68	Low
27	Law and Accounting Activities	69-71	High
28	Training and Development of Science	72	High
29	Advertising and Market Research, and Other Business Activities	73-75	High
30	Office Administration and Business Support Activities	77-82	High
31	Government Administration and Defense	84	Medium- High
32	Education	85	Medium- Low
33	Human Health Activities	86	Medium- Low
34	Activities of the Shelter and Social Work	87-88	Medium- Low
35	Arts, Entertainment, and Recreation	90-93	Medium- High
36	Other Service Activities	94-96	High

Source: OECD, 2018

The Digital Intensity Sector Taxonomy in Table 1 can be considered for application in Indonesia, as the sampling encompasses not only developed countries but also developing countries like Indonesia. Indicators that include Indonesia in the sample are ICT purchases and robot use. For other indicators, Calvino also considers developing countries as observation samples. This demonstrates that the digital intensity sector taxonomy can be used globally.

RESEARCH METHODOLOGY

Using quantitative methods, this research focuses on the research objectives, including analyzing the tendency of higher education graduates with a vertical mismatch to work in high digital intensity (HDI) sectors. The following presents the data sources, analytical framework, units of analysis, and model specifications to answer the research questions.

The data used in this study is the 2018 National Labor Force Survey (Sakernas) data. Sakernas is a special survey that can describe the general state of employment between census periods. The 2018 Annual Sakernas was conducted throughout Indonesia with a sample of approximately 200,000 households,spread across 20,000 census blocks across all provinces in both urban and rural areas, and was intended to produce estimated figures down to the district/municipality level.

This study analyzed a sample consisting of individuals aged 18 to 64 years who were working, with a minimum education level of Diploma-1 or higher education, excluding members of the armed forces and police from the sample.

Following are research models that will answer research question:

$$\begin{aligned} Prob\ (Y = HDI\ Sector_t = 1) &= \alpha_0 + \alpha_1 vmismatch_t \\ &+ \alpha_1 Age_t + \alpha_2 Age_t^2 \\ &+ \alpha_6 gender_t + \alpha_7 Urban_t \\ &+ \alpha_8 regian + \alpha_9 edu_t \\ &+ +\alpha_7 formal_t + \alpha_8 occup \\ &+ \alpha_9 work\_stat_t \\ &+ mworkinghours + \varepsilon \end{aligned}$$

Control variables of this study are age, age-squared, dummy of gender, dummy of urban, dummy of region, dummy of education level, dummy of formality, dummy of type of occupation, dummy of status of work, dummy of sector of employment, and monthly working hour.

RESULT AND DISCUSSION

The following are the results of data processing using logit with the dependent variable being the probability of workers entering the high digital intensity (HDI) sector. A key finding of this study is that vertical mismatch significantly impacts an individual's likelihood of working in high-digital- intensity (HDI) sectors.

Table 2: Dependent Variable: HDI-Sector

	(1)
VARIABLES	General Model
Well-matched (Ref)	
1.underqualified	-0.0610***
	(0.00982)
2.overqualified	-0.184***
	(0.00866)
1.gender	-0.0690***
	(0.00652)
1.train	0.0128
	(0.00800)
age	0.000947
	(0.00163)
age2	-3.95e-05**
	(1.98e-05)
1.mar	-0.00627
	(0.00847)
1.urban	0.139***
	(0.00629)
1.exp	-0.0178***
	(0.00627)
1.internet	0.138***
	(0.00721)
Observations	28,457

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A key finding of this study is that vertical mismatch significantly impacts an individual's likelihood of working in high-digital-intensity (HDI) sectors. Compared to the well-matched group, underqualified workers are 6.10% less likely to work in these sectors, while overqualified workers are even less likely, at 18.4%. These findings indicate that both under and over education relative to job needs negatively impact workforce participation in the digital sector, but the greatest penalty is experienced by the overqualified group.

This phenomenon opens up the opportunity for deeper analysis regarding the characteristics of digital jobs and the dynamics of demand. The decline in opportunities for overqualified groups can be explained by the mismatch between expectations and the needs of the digital sector. Overqualified individuals often experience skill underutilization and potential job dissatisfaction, making them less attractive to digital sector employers seeking efficiency and adaptability *(Verhaest & Omey, 2009)*.

This is reinforced by other studies finding that overeducation negatively impacts job matching quality and individual productivity, particularly in rapidly changing sectors such as the digital economy *(Green & Zhu, 2010)*.

On the other hand, although underqualified groups also face obstacles, the penalties they experience are statistically smaller than those of overqualified groups. One plausible explanation is that underqualified groups can still be absorbed into digital-based jobs that are non-cognitive or operational, such as application-based logistics jobs, digital courier services, or content moderation — which can be categorized as blue-collar digital jobs—. Research suggests that the growth of the platform economy has created many positions that require the use of technology (for example, through digital applications), but do not always require higher educational qualifications *(Chishti & Barberis, 2020; ILO, 2021)*. In other words, jobs that utilize technology are not only based on digital high-skills, but also include more manual work fields that are still connected to digital systems.

Consequently, underqualification does not necessarily mean complete exclusion from the digital sector, especially in the context of Indonesia, which has a rapidly growing informal sector and digital-based services. Conversely, overqualification can actually be a barrier when available jobs are deemed "incommensurate" with a worker's formal educational background, leading to mismatched expectations and rejection from both workers and employers.

These findings underscore the importance of a more flexible approach to defining digital work readiness, taking into account the diverse forms of digital work beyond the high-tech stereotype. Governments and educational institutions need to recognize that the digital economy is driven not only by engineers and programmers, but also by a diverse group of technology-using workers who may not have advanced degrees but are nonetheless essential to the digital value chain.

Other research findings from a demographic perspective show that gender, age, marital status, location of residence, work experience, and internet use at work is an important determinant of an individual's chances of working in sectors with high digital intensity. Logit regression analysis indicates that these factors shape uneven patterns of digital participation opportunities across social groups.

First, the results show that men have a higher probability of working in high-digital-intensity sectors than women. This finding is consistent with other findings highlighting the existence of a digital gender divide, where women face barriers in accessing and utilizing digital technology, whether due to social norms, limited skills, or double burdens in the household *(Hilbert, 2011; UNESCO, 2020)*. Other studies also confirm that gender inequality in access to information technology reinforces inequality in the digital workforce *(Huyer, 2015)*.

Second, training or participation in skills enhancement programs has been shown to contribute positively and significantly to opportunities for entry into high-digital-intensity sectors. This aligns with findings that reskilling and upskilling are crucial in supporting the workforce's transition to the digital economy, particularly in developing countries *(Bodewig, Ikeda & Stacey, 2018)*. The ILO also emphasized the importance of digital skills-based training as a crucial component of an inclusive national employment development strategy.

Third, the pattern of the relationship between age and job opportunities in high digital intensity sectors follows a non-linear pattern, where the probability increases at young and middle ages, but decreases after a certain point. This finding confirms studies showing that adaptation to new technologies tends to be higher among younger workers due to earlier exposure to digital innovation, while older workers face technological obsolescence and adoption resistance *(Greenan, L'Horty & Mairesse, 2014)*. This insicates the need for a crossgenerational approach in digital transformation policies.

Marital status also influences participation in the digital workforce. Results show that married individuals are less likely to be involved in this sector. This is likely related to the need for flexibility in work time and location in the digital sector, which does not always align with the preferences of workers with families. Studies note that digital jobs are often flexible, but not always stable, making them less attractive to individuals with family responsibilities *(Ravazzini & Chavez, 2021)*.

Furthermore, living in urban areas significantly increases the chances of entering high-digital-intensity sectors. This finding is supported by the OECD (2019) and the World Bank (2021). which states that digitalization tends to be concentrated in urban centers, where ICT (information and communications technology) infrastructure, internet connectivity, and digital job opportunities are more widely available. This emphasizes the existence of a digital urban bias in the distribution of digital jobs.

The work experience variable also has a positive effect, although it is not always significant. strong. Other research shows that work experience contributes to the accumulation of non-formal skills that can be applied in a digital context, although the added value depends on the type of experience and relevance to the needs of the digital industry *(Autor, Levy & Murnane, 2003)*.

The results show that workers who have used the internet in their work have a significantly higher chance of being in the digital sector. This aligns with the OECD (2020) study. Other findings emphasize that digital exposure, or direct involvement with digital technology, is a strong indicator of participation in the digital economy. The internet is not only a work tool but also an indicator of the type of work itself, especially in the context of platform-based work, data analytics, digital marketing, and remote work *(Qiang et al., 2021)*.

CONCLUSION

This study shows that a vertical mismatch between education and job type significantly impacts employment opportunities in high digital intensity (HDI) sectors. Compared to well-matched workers, underqualified workers have a 6.10% lower chance, while overqualified workers face a higher penalty of 18.4%. However, the smaller penalty for the underqualified group may indicate that some of them are still absorbed in the digital sector through operational-based or blue-collar jobs that do not require higher educational qualifications but remain within the digital ecosystem. This finding confirms that the most important determining factor is not just education level, but the match of skills to sector needs.

Furthermore, individual characteristics also influence the probability of working in the SID sector. Men, younger individuals, unmarried individuals, those living in urban areas, those with work experience, and those using the internet for work are more likely to enter this sector. These findings reflect structural inequalities in access to digital jobs and the need for policies that support strengthening digital literacy and equitable access to skills training relevant to labor market needs.

REFERENCES

Abdulla, K. (2024) 'Quantifying the productivity effects of education-job mismatch: a cross-country analysis', *Education Economics*, pp. 1–18.

Allen, J. & Van der Velden, R. (2001) 'Educational mismatches versus skill mismatches: Effects on wages, job satisfaction, and on-the-job search', *Oxford Economic Papers*, 53(3), pp. 434–452. doi: 10.1093/oep/53.3.434.

Autor, D.H., Levy, F. & Murnane, R.J. (2003) 'The skill content of recent technological change: An empirical exploration', *Quarterly Journal of Economics*, 118(4), pp. 1279–1333. doi: 10.1162/003355303322552801.

Büchel, F. & Mertens, A. (2004) 'Overeducation, undereducation, and the theory of career mobility', *Applied Economics*, 36(8), pp. 803–816.

Becker, G.S. (1964) *Human capital: A theoretical and empirical analysis, with special reference to education*. Chicago: University of Chicago Press.

Bodewig, C., Ikeda, Y. & Stacey, D. (2018) *Skilling up Indonesia: Unlocking the potential of the workforce*. Washington, DC: The World Bank. doi: 10.1596/978-1-4648- 1342-2.

Calvino, F., Criscuolo, C., Marcolin, L. & Squicciarini, M. (2018) *A taxonomy of digital-intensive sectors*. OECD Science, Technology and Industry Working Papers, 2018/14. doi: 10.1787/f404736a-en.

Chishti, S. & Barberis, J. (2020) *The future of fintech: Integrating finance and technology in financial services*. Wiley.

Das, K., Gryseels, M., Sudhir, P. & Tan, K.T. (2016) *Unlocking Indonesia's digital opportunity*. McKinsey & Company.

Green, F. & Zhu, Y. (2010) 'Overqualification, job dissatisfaction, and increasing dispersion in the returns to graduate education', *Oxford Economic Papers*, 62(4), pp. 740–763. doi: 10.1093/oep/gpq002.

Greenan, N., L'Horty, Y. & Mairesse, J. (2014) 'Information technology and changes in the skills of French workers', *Journal of Labour Economics*, 32(3), pp. 549–585. doi: 10.1086/675235.

Hartog, J. (2000) 'Over-education and earnings: Where are we, where should we go?', *Economics of Education Review*, 19(2), pp. 131–147. doi: 10.1016/S0272-7757(99)00050-3.

Hilbert, M. (2011) 'Digital gender divide or technologically empowered women in developing countries? A typical case of lies, damned lies, and statistics', *Women's Studies International Forum*, 34(6), pp. 479-489. doi: 10.1016/j.wsif.2011.07.001.

Hirao, T. (2024) *Horizontal Education-Job Mismatch in a Medium-Sized Japanese Company*. Center for Open Science.

Huyer, S. (2015) 'Is the gender gap narrowing in science and engineering?', in *UNESCO Science Report: Towards 2030*, pp. 85–103.

International Labour Organization (ILO). (2020) *Global employment trends for youth 2020: Technology and the future of jobs*. Geneva: ILO Publishing.

International Labour Organization (ILO). (2021) *World Employment and Social Outlook 2021: The role of digital labour platforms in transforming the world of work*. Geneva: ILO Publishing.

Levels, M., Van der Velden, R. & Di Stasio, V. (2014) 'From school to fitting work: How education-to-job matching of European school leavers is related to educational system characteristics', *Acta Sociologica*, 57(4), pp. 341–361.

McGuinness, S. & Sloane, P.J. (2011) 'Labour market mismatch among UK graduates: An analysis using REFLEX data', *Economics of Education Review*, 30(1), pp.130–145. doi: 10.1016/j.econedurev.2010.07.006.

Mincer, J. (1974) *Schooling, experience, and earnings*. New York: Columbia University Press.

Montt, G. (2017) 'Field-of-study mismatch and overqualification: labour market correlates and their wage penalty', *IZA Journal of Labor Economics*, 6, pp. 1–20.

OECD (2019) *Measuring the digital transformation: A roadmap for the future*. Paris: OECD Publishing. doi: 10.1787/9789264311992-en.

OECD (2020) *OECD Employment Outlook 2020: Worker security and the COVID-19 crisis*. Paris: OECD Publishing. doi: 10.1787/1686c758-en.

Prospera (2019) *Capturing Indonesia's Automation Potential*. Prospera Indonesia.

Qiang, C.Z.-W., Yamamichi, M., Hausman, V., Altman, D. & Frydrych, J. (2021) *Digital economy for Indonesia: Policy levers for digital transformation*.

Quintini, G. (2011) *Right for the Job: Over-qualified or Under-skilled?* OECD Publishing. Washington, DC: World Bank Group. doi: 10.1596/35350.

Ravazzini, L. & Chavez, C. (2021) 'Digitalization and the future of work: Are married women left behind?', *Journal of Economic Inequality*, 19, pp. 165–188. doi: 10.1007/s10888-020-09447-z.

Salas-Velasco, M. (2021) 'Mapping the (mis)match of university degrees in the graduate labor market', *Journal for Labour Market Research*, 55(1), p. 14.

Suryadarma, D., Widyanti, W., Suryahadi, A. & Sumarto, S. (2006) *From access to income: Regional and ethnic inequality in Indonesia*. SMERU Research Institute Working Paper. Available at: https://smeru.or.id/en/content/access-income-regional-and-ethnic-inequality-indonesia.

Tsang, M.C. & Levin, H.M. (1985) 'The economics of overeducation', *Economics of Education Review*, 4(2), pp. 93–104.

UNESCO (2020) *Gender and ICTs: Policy brief*. Paris: United Nations Educational, Scientific and Cultural Organization. Available at: https://unesdoc.unesco.org/ark:/48223/pf0000375626

Verhaest, D. & Omey, E. (2009) 'Objective over-education and worker well-being: A shadow price approach', *Journal of Economic Psychology*, 30(3), pp. 469–481. doi: 10.1016/j.joep.2009.01.002.

World Bank (2021) *Digital Indonesia: Unlocking the potential of the digital economy for inclusive development*. Available at: https://documents.worldbank.org/en/publication/documentreports/documentdetail/430401628145088349

Yeo, J.Z. & Maani, S.A. (2017) 'Educational mismatches and earnings in the New Zealand labour market', *New Zealand Economic Papers*, 51(1), pp. 28–48.