The Future of Human Work and The Knowledge Economy

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Abstract:
This study examines and investigates internet technology literacy, unemployment, education, and job participation in Indonesia to understand the role of education in human work in the future. This study took 21 years, from 2000 to 2020 by modeling "autoregressive vectors" to understand the causal relationship between variables. This research is based on secondary data from the world bank and we use the variables of internet literacy, job participation, education, and unemployment in Indonesia. We found that technological developments are proven not to be significantly related to unemployment as long as education and work participation accompany technological developments. This is not surprising because the loss of type of work due to the emergence of technology has given birth to new jobs that are more diverse so that unemployed workers as long as they are willing to upgrade themselves following technological developments can switch to new jobs.

Keywords: Internet Technology Literacy, Unemployment, Education, Job Participation
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Background

The future of human work related to the development of the knowledge economy, technological developments, and artificial intelligence tools (Malik, Tripathi, Kar, & Gupta, 2022). The role of employees in relation to the economy in the future will undergo various changes (Kurt, 2019). Humans may lose their jobs in the future due to technological changes and changes in human life, but what must be noted is that alternative jobs have emerged along with the development of technology (Rusmingsih, Widarni, & Bawono, 2021). Technology is doing its job and trying to find a place for it in the human world, and the knowledge economy has provided it in the technological world of the world (Williamson, Eynon, & Potter, 2020). Unusual work ideas are crystallized when, in simulations, models of the world's leading human minds are transmitted in several scientific and sports fields. Artificial intelligence is developing better and better from time to time so that artificial intelligence can replace various human occupations (Widarni, & Bawono, 2021).

Artificial intelligence and increasingly sophisticated and automated robotization threaten to take humans out of their jobs (Vu & Lim, 2022). Machines programmed in the world of artificial intelligence perform fully human functions, and even do so without any complications or the slightest cost (Helo & Hao, 2022). Therefore, its acceptance is possible, and people who have money and businesses are eager to do so. One machine can do the work of many people so technology can offer advantages in the business sector (Mutascu,2021).

Large factories in the application of artificial intelligence and robotization can create a huge unemployment crisis, as can other institutions in all fields and sectors (Bhushan, 2021). The knowledge economy is an economic alternative that allows humans to be actively involved and is difficult to replace by artificial intelligence, namely human creativity (Holford, 2019). And since the knowledge economy's biggest distinguishing trait is that it is decentralized and improving in all sectors, including technology, as the digital economy is doing. In it, and earn money through it, without being tied to a time in a place, or at a certain time (Frolov & Lavrentyeva, 2019). The knowledge economy enables humans to generate income across countries (Ojanperä, Graham, & Zook, 2019). There is also a serious trend in the private sector to invest in research and development in response to the negative effects of technological waves on all types of employment sectors, which reinforces the idea of achieving a knowledge society in return (Fu, Bao, Xie, & Fu,2021).

Agriculture remains the closest economic resource to the atmosphere of human civilization, and the sector's innate origins are by using technological systems to develop agricultural work (Gordon, Davila, & Riedy, 2022). The technology boom will cover agriculture and human work in it will be facilitated or replaced by providing more comprehensive machines in the field (Lowenberg-DeBoer, Huang, Grigoriadis, & Blackmore, 2020). The development of robots and artificial intelligence applications threatens many jobs that require technical skills. Therefore, technology requires individuals to study the technology they produce. Human skills and creativity enable the performance of many cognitive functions that require higher education to improve (Focacci,2021 ; Drean,2021).

Robotization has the potential to create massive unemployment at all skill levels, stagnant or lower wages for most workers, and a growing concentration of income and wealth for capitalists in the world economy. This in turn leads to lower consumer spending and lower economic growth as the largest share of additional income, which is sufficient to impoverish the population from purchasing products and services generated by the knowledge economy (Sequeira, Garrido, & Santos,2021).

Superior technology, resources, geography, and history, if used responsibly and transparently produce a strong economy (Cordery & Hay, 2022). Where the natural economic surplus flows into the expansion of the use of technology, since technology is an important element of human civilization, particularly in terms of economics and new financing sources (Sasongko, Bawono, & Prabowo, 2021). Apart from all that, we must not forget the impact of values in society on the application of technology and its products, because it will not let members of society get lost in pursuing global technological developments. Technological developments make human work easier (Achmad, 2021). But technological developments or technological revolutions end various types of work and create new jobs (Widarni, Prestianawati, Bawono, 2020). This study examines and investigates internet technology literacy, unemployment, education, and job participation in Indonesia to understand the role of education in human work in the future.

Research methods

This study took 21 years, from 2000 to 2020 by modeling "autoregressive vectors" to understand the causal relationship between variables. This research is based on secondary data from the world bank and we use the variables of internet literacy, job participation, education, and unemployment in Indonesia.

To evaluate the causal relationship between internet literacy, job participation, education, and unemployment in Indonesia, the following multivariate regression model was used:

$IL_t = \beta_0 + \beta_1 JP_t + \beta_2 E_t + \beta_3 UE_t + e_t$ eql 1
$JP_t = \beta_0 + \beta_1 IL_t + \beta_2 E_t + \beta_3 UE_t + e_t$ eql 2
$E_t = \beta_0 + \beta_1 IL_t + \beta_2 JP_t + \beta_3 UE_t + e_t$ eql 3
$UE_t = \beta_0 + \beta_1 IL_t + \beta_2 JP_t + \beta_3 E_t + e_t$ eql 4

Description :
IL : Internet literacy
JP : Job participation
E : education
UE : Unemployment
e : error term
t : time series
β : the magnitude of the effect of causality
eql: equation
This study uses vector calculations where each regression relationship will be brought together so that each variable will alternately become the dependent variable and the independent variable. The zero theory of Dickey-Fuller, taken from the PP test, and p=1 is the formula in Δyt = (ρ – 1)yt-1 + ut, in which Δ – for the first time different operators. This research used the following equation for the "unit root test":
$\Delta Y_1 = \alpha_0 + \beta_0 T + \beta_1 Y_{t-1} + \sum_{i-1}^{q} \alpha_1 \Delta Y_{t-1} + e_t$
Description:
Y as the variable is being examined for unit root
T as the variable which indicates the "linear trend," the "lag difference" means is $\Delta Yt-1$,
$\alpha 0$ are shown as "constant term," with the
"t" as a "time trend" indicator.
The null and alternative hypotheses for the "unit root test" are as follows:
$H_0: \alpha=0$
$H_1: \alpha\neq0$

Results and Discussion

Before fulfilling one of the causality and VAR assumptions, a stationarity test is necessary. The ADF Test takes into consideration the likelihood of autocorrelation in the error term if the series being evaluated is non-stationary. The following are the results of the unit root test:

Table 1. ADF's Unit Root Test on IL, E, JP, and UE data in Indonesia

Variable	Unit Root	Include in the examination Equation	Statistics for the ADF Test	5% Critical Value	Description
Internet Literacy (IL)	Level	Intercept	6.626153	1.0000	
	First Diff	Intercept	-0.254496	0.9143	
	Second Diff	Intercept	-7.999192	0.0000	Stationer

Education (E)	Level	Intercept	0.330179	0.9721	
	First Diff	Intercept	-5.019844	0.0012	Stationer
Job Participation (JP)	Level	Intercept	-2.412304	0.1510	
	First Diff	Intercept	-4.563916	0.0024	Stationer
Unemployment (UE)	Level	Intercept	-0.606491	0.8482	
	First Diff	Intercept	-3.886074	0.0089	Stationer

IL data is stationary at the second difference, and E, JP, and UE data at the first difference level are stationary. The ADF test is worth -7.999192 with a critical value of 0.0000. Smaller than the p-value, in this case, the IL data shows stationary in the second difference compared to the original data. The same thing happened to E, JP, and EU data which were stationary at the first difference level. From here we can take the next step in determining vector analysis. The VAR test and the causality test both need the right lag length sensitivity. It is crucial to select the optimum acceptable pause period before doing a VAR or causality test study. In this experiment, the shortest or lowest Akaike Information Criteria (AIC) was used to identify the appropriate time lag. The gap length ranges from 0 to 2 since the data used in this test comprises annual data throughout a 21-year period. On an annual basis, this lag is considered long enough to distinguish IL, JP, E, and UE.

Table 2. Optimum lag test at Lag 0 to 2 IL, JP, E, and UE data in Indonesia

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-163.6496	NA	542.5123	17.64733	17.84616	17.68098
1	-99.58369	94.41297*	3.621800*	12.58776*	13.58190*	12.75601*
2	-87.32780	12.90093	7.094855	12.98187	14.77134	13.28472

Table 2 shows the findings of the Optimum Lag test. At Lag 0 to 2, the AIC value suggests that the length of the Lag IL, JP, E, and UE variables is at LR, FPE, AIC, SC, and HQ at Lag 1. Because the findings of the five components are identical, lag 1 will be selected. The interactions between IL, JP, E, and UE are shown in this figure, during this period. Based on the data, there is no preliminary effect for the five variables, so according to the FPE requirements of 3.621800, the best lag is at lag 1. One of the differences between the VECM and the VAR models is that the variables in the VECM model must have a cointegration link. To determine the cointegration of all variables, the test of Johansen Cointegration is used.

Table 3. Cointegration test

Hypothesized	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.818838	60.56438	47.85613	0.0021
At most 1	0.587605	28.10547	29.79707	0.0774
At most 2	0.432897	11.27575	15.49471	0.1951

At most 3	0.025904	0.498668	3.841466	0.4801

The results of the cointegration test are shown in Table 3. The data show that the three variables have a long-term reciprocal relationship or cointegration. Based on these results, the VECM model might be utilized to continue the model estimation process. The VECM model is a constrained VAR model that accounts for short-term dynamics while limiting the variables to long-term linkages (cointegration).

Table 4. VECM model analysis

Cointegrating Eq:	CointEq1			
IL(-1)	1.000000			
JP(-1)	-0.625341			
	(0.42065)			
	[-1.48659]			
E(-1)	-3.003056			
	(0.33066)			
	[-9.08194]			
UE(-1)	-0.248007			
	(0.57408)			
	[-0.43201]			
C	150.5887			
Error Correction:	D(IL)	D(JP)	D(E)	D(UE)
CointEq1	0.321537	-0.064668	0.456357	-0.068953
	(0.13855)	(0.09226)	(0.11023)	(0.04591)
	[2.32077]	[-0.70091]	[4.14012]	[-1.50198]
D(IL(-1))	0.099661	0.196770	-0.621272	0.125851
	(0.36491)	(0.24300)	(0.29032)	(0.12091)
	[0.27311]	[0.80974]	[-2.13995]	[1.04082]
D(JP(-1))	0.014186	-0.141417	-0.300867	0.060862
	(0.48592)	(0.32359)	(0.38660)	(0.16101)
	[0.02919]	[-0.43702]	[-0.77824]	[0.37800]
D(E(-1))	0.407083	0.047636	0.320717	-0.054649
	(0.35160)	(0.23414)	(0.27973)	(0.11650)
	[1.15782]	[0.20345]	[1.14653]	[-0.46908]
D(UE(-1))	1.013901	-0.185399	0.978780	-0.241383
	(0.94630)	(0.63017)	(0.75287)	(0.31356)

	[1.07144]	[-0.29421]	[1.30007]	[-0.76981]
C	2.359226	-0.754729	2.079101	-0.391915
	(0.93501)	(0.62265)	(0.74389)	(0.30982)
	[2.52321]	[-1.21212]	[2.79491]	[-1.26498]
R-squared	0.648781	0.178467	0.647242	0.176439
Adj. R-squared	0.513697	-0.137508	0.511566	-0.140315
Sum sq. resids	46.95846	20.82436	29.72334	5.155856
S.E. equation	1.900576	1.265652	1.512088	0.629765
F-statistic	4.802789	0.564814	4.770487	0.557023
Log likelihood	-35.55566	-27.83084	-31.21102	-14.56893
Akaike AIC	4.374280	3.561141	3.916950	2.165150
Schwarz SC	4.672524	3.859385	4.215194	2.463394
Mean dependent	2.721467	-0.188947	0.679426	-0.096316
S.D. dependent	2.725409	1.186689	2.163585	0.589748

The presentation of the VECM model can be seen in Table 4. The results shown in Table 4 can be seen that the table above shows the long-term relationship between the four variables, namely internet literacy, job participation, education, and unemployment. While at the bottom of the table is the interpretation of the short-term relationship between the four variables. In the table above, it can be seen that the variables of work participation, education, and unemployment have an effect on internet literacy.

The estimation results show the values of -1.48659, -9.08194, and -0.43201. The coefficient of work participation is -0.625341, meaning that an increase in work participation of 1% will affect internet literacy by -0.625341%. Likewise, the education variable has a coefficient of -3.003056, meaning that every 1% increase in education will affect the increase in internet literacy by -3.003056%. Furthermore, the unemployment variable has a coefficient of -0.248007, meaning that every 1% increase in unemployment will affect an increase in internet literacy by -0.248007%. While in Table 4 at the bottom it can be seen the short-term relationship between the three variables. In Table 4 it can also be seen that the largest R-square value is found in the internet literacy variable, which is 0.648781.

Table 5. The Granger Causality Analysis

Null Hypothesis:	Obs	F-Statistic	Prob.
JP does not Granger Cause IL	20	1.24319	0.2804
IL does not Granger Cause JP		0.58147	0.4562
E does not Granger Cause IL	20	0.25726	0.6185
IL does not Granger Cause E		18.0644	0.0005
UE does not Granger Cause IL	20	0.13159	0.7213
IL does not Granger Cause UE		0.36329	0.5546
E does not Granger Cause JP	20	0.00224	0.9628
JP does not Granger Cause E		0.02275	0.8819
UE does not Granger Cause JP	20	1.89101	0.1869
JP does not Granger Cause UE		1.55093	0.2299
UE does not Granger Cause E	20	4.23154	0.0554

E does not Granger Cause UE	0.12188	0.7313

The results of the Granger causality test analysis can be seen in Table 5. The results show that the causal relationship only occurs on the internet literacy variable, does not affect education, with a probability value of 0.0005. While the causality relationship between other variables is not significant.

Conclusion

Technological developments are proven not to be significantly related to unemployment as long as education and work participation accompany technological developments. This is not surprising because the loss of type of work due to the emergence of technology has given birth to new jobs that are more diverse so that unemployed workers as long as they are willing to upgrade themselves following technological developments can switch to new jobs.

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