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Nonlinear Impact of Information Technology on Gross Regional Domestic Product : A Generalized Additive Model Approach

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Abstract

Decades of developments in information and communication technology (ICT) have, for better and worse, disrupted economies globally. The GDP of a country is the most important indicator in the analysis of economic growth because through changes in this indicator, the success of macroeconomic development can be seen. Using Indonesian data spanning 2014–2019, this study documents the influence of information technology (IT), local government expenditures, the labor force's size, and human capital on gross regional domestic product in East Java, one of provinces in Indonesia. We proxy IT in a generalized additive model using the number of cellular phone users. We utilized Ramsey test each predictor variable for linearity with the response variable; all have a nonlinear relation. The model shows that all variables except IT are significant with a coefficient of determination of 93.6%. Human capital, local government expenditures, and the labor force's size exhibit the largest effect on gross regional domestic product.

Keywords: Education, Generalized Additive Model, Government Expenditures, Information Technology, labor.

1. Introduction

Decades of developments in information and communication technology (ICT) have, for better and worse, disrupted economies globally. That technology catalyzes economic growth **(Ferdinand, 2013)** is why Indonesia's Master Plan for the Acceleration and Expansion of Indonesian Economic Development establishes a special institution to increase the role of ICT nationally **(Coordinating Ministry for Economic Affairs, 2011)**. Indonesia's Central Bureau of Statistics (BPS) indicates that ICT, which covers all telecommunications activities including cellular phone use, accounted for 3.77% of national gross domestic product (GDP) in 2018. The GDP of a country is the most important indicator in the analysis of economic growth because through changes in this indicator, the success of macroeconomic development can be seen **(Henderson et.al, 2012)**. Studies demonstrate a positive relation between per capita cell phone use and economic growth, particularly in low-income areas.

Strengthening the ICT sector needs to be done in low-income areas such as East Java Province, according to empirical evidence of economic development inequalities between provinces based on the Klassen typology carried out **(Purnama & Hitoshi, 2018)** East Java Province is an area that is included in the High Growth But Low Income (HL) quadrant and this study shows that the regional economy in the HL quadrant is positively affected by telephone penetration **(Purnama & Hitoshi, 2018)**.

This study examines how ICT, which is represented by the number of cellular phone users, affects East Java's GDP from 2014 to 2019. Previously, **Wibowo et.al** in 2020 conducted research related to the influence of technology on the economy using Main Component Panel Regression, based on the best model obtained showing that ICT has a positive impact on economic growth. Modeling to determine the relationship between variables, namely the response variable with the predictor does not always follow the assumption of linearity. and normally distributed, which is why **Hastie and Tibshirani (1986)** adapted the additive model into a generalized linear model known as the generalized additive model (GAM). GAM stands for Generalized Linear Model (GLM) which is a development of linear regression to overcome response variables that are not normally distributed but have an exponential distribution and have a linear relationship, while GAM is more flexible in its use in cases where there is no linear relationship between variables. response and predictor variables.

Based on the description above, in this study, we use a general additive model (GAM), which aims to compare its effects and three other contributors to the GRDP: investment (represented by public expenditure), size of the labor force by the growth of Solow the theory of (Barbosa, 2018), and human capital (represented by the average number of years of education of workers), by **Schultz (1961)** and **Frank et al. (2007)**. The GAM model was chosen because it is more flexible than the additive model, the GAM model can accept errors such as non-normality, non-linear relationships, and autocorrelation variables **(Ananda, 2019)**.

2. Literature Review

Economic growth is a function of productive inputs conventionally grouped as capital, size of the labor force, and technology. The neoclassical production function describes how inputs yield output measured by GDP **(Leasiwal, 2013)**. Economic theory argues that national economic growth depends on growth in investment capital, size of the workforce, human capital, and advances in technology. By fostering technological innovation and elevating workers' human capital, education fosters economic growth **(Zhou and Luo, 2018)**.

In neoclassical growth theory, technological advances explain long-term economic growth **(Reza and Widodo, 2013)**. Technological advances are influenced by human capital through education **(Leasiwal, 2013)**. Technology is a concept that is akin to a black box wherein resources yield goods and services **(Romer, 1990)**. Given the breadth of the concept, the present study focuses on one aspect in particular, namely, cellular phone ownership.

Capital accumulated for investment is considered the foundation of economic growth. Investment depends on savings obtained from income and diverted from consumption. Technological progress encompasses entire information systems, organization, and production techniques. Technology raises output per unit of input in production, thereby trimming expenditures on labor and capital. Increases in population foster larger numbers of workers **(Çalışkan, 2015)**. Technology makes production faster, more precise, more efficient, and less expensive. The results of the research by **Wibowo et.al (2020)** regarding modeling the influence of ICT on economic growth in the industrial revolution 4.0 era with the principal component panel regression approach, the best model is the fixed effects model which shows that all predictor variables have positive coefficients. This means that ICT still has a positive impact on economic growth. Research on how ICT affects Indonesia's economic growth through linear regression with ordinary least squares by **Hariani (2017)** shows that gross fixed capital formation, number of Internet users, and size of the working-age population significantly and positively affect Indonesia's economic growth. In his study of technological growth and total factor productivity, **Ferdinan (2013)** showed that Indonesia's technological development was advanced by 0.87% but contributed 30.48% to economic growth from 1981 to 2012.

Lubis and Febrianty (2018) showed that broadband subscriptions and the number of nternet users enhance GDP through impulse response functions. Using panel data for 34 Indonesian provinces from 2009 to 2017, **Purnama and Mitomo's (2018)** fixed-effects model indicates cellular phone adoption correlates positively with per capita economic growth, especially in low-income areas. As additional, **Tankari (2018)** conducted study in Niger and showed that the mobile phone ownership has significant impact in reducing food poverty.

3. Data and Measures

The data used comes from data from the Indonesian Central Bureau of Statistics (BPS) for 38 districts of East Java Province during the period 2014-2019. The variables are the regional gross domestic product (GDP) of the province of East Java at constant prices, local government expenditure (exp), number of the workforce (labor), number of mobile phone users (telephone), and the average education of workers (human). The research variables are presented in Table 1 below.

Table.1. Research Variable

Variable type	Variable
Response Variable	- Gross Regional Domestic Product (GRDP) (Y)
Predictor Variable	- The size of the labor force (labor) (X1) - Local government expenditures (exp) (X_2) - The number of cellular phone users (phone) (X_3) - Workers' average education (human) (X_4)

4. Analysis Method

This section will explain the analytical methods that will be used in this study. First, we assessed linearity and nonlinearity between response and predictor variables by a Ramsey test, using library lmtest in R software by **(Zeileis and Hothorn, 2002)**. A linearity test makes it possible to determine whether the model used is a linear function of the parametric function or not. This test was developed by **Ramsey in 1969** and is commonly referred to as the General Specification Test or RESET. This test aims to produce an F_{value}. The hypothesis of the Ramsey Test is as follows.

H_0: There is a linear relationship between predictor variables and response variables

H_1: There is no linear relationship between predictor variables and response variables

The following is the procedure for obtaining the F_{value} statistic:

1. Obtain the fitted value of the response variable by performing linear regression analysis.
2. The squared variable is regressed with the original model as a new predictor variable.
3. Calculation of F_{value}

$$F_{value} = \frac{(R^2_{new} - R^2_{old})/p}{(1 - R^2_{new})/(n-k)} \tag{1}$$

with

p : number of recently entered predictor variables

n : amount of data

k : number of parameters in the new regression model

R^2 *new* : the R^2 value of the new regression equation

R^2 *old* : the R^2 value of the old regression equation

critical region : Reject the Null hypothesis (H_0) if F_{value} in a test is larger than $F_{statistic}$ ($F_{value} > F_{table(\alpha;k,n-k-1)}$).

The next analysis is correlation testing. Correlation testing is a statistical method used to measure the magnitude of the linear relationship between two variables with one value called the correlation coefficient **(Walpole, 2007)**. The correlation coefficient (r_{xy}) is an indicator of the relationship between 2 variables **(Draper and Smith, 1992)**. The correlations for the predictor variable (x) and response (y) are formulated as follows

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{2}$$

Correlation coefficient values range in interval $-1 \leq \rho \leq 1$. That is, the closer to 1, the close relationship between the two variables is linear and vice versa. Meanwhile, if the correlation result is 0, then the relationship between the two variables is linearly weak, where x and y are the observed variables and n is the number of observations. Hypothesis testing used is the following

H_0: $\rho = 0$ (no correlation between x and y)

H_1: $\rho \neq 0$ (there is a correlation between x and y) with the t test statistic as follows.

$$t_{value} = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}} \tag{3}$$

Critical region: Reject the H_0 if $|t_{value}|$ in a test is larger than $t_{statistic}$ ($|t_{value}| > t_{table(\alpha/2;n-2)}$).

The next method is the smoothing spline. Suppose there are data pairs (t_i,y_i), $i=1,2, \ldots, n$ and $a \leq t_1 \leq \ldots \leq t_n \leq b$. Then a general regression model is formed as follows.

$$y_i = f(t_i) + \varepsilon_i \tag{4}$$

with an identical and independent residual ε, and $f(t_i)$ is any unknown function. Spline smoothing is obtained if the estimation of f in model (4) is obtained by minimizing the penalized least square

$$s(f) = n^{-1}\sum_{i=1}^{n}\left(y_i - f(t_i)\right)^2 + \lambda\int_a^b \left(f^{(m)}\right)^2 dt \tag{5}$$

with $a \leq t_1 \leq t_2 \leq \ldots \leq t_n \leq b$.

The first term is the sum of residual squares, as in ordinary least squares, and the second term is the penalty for the function f with λ as the smoothing parameter. So this approach is also called the least penalized place. The solution (5) is a natural spline polynomial of order ($2m$-1), which no longer interpolates $y_1,y_2,\ldots,y_n$, but transmits it smoothly with the smoothing parameter λ. The smoothing parameter λ plays a role in regulating the smoothness of function f. If $\lambda \to 0$, then the form of the function f will become coarser, by interpolating the observation points. Conversely, if $\lambda \to \infty$, then the form of the function f will approach a straight line, as in linear regression. Illustration of the effect of a smoothing parameter λ on the shape of the curve f, shown in Figure 1 and Figure 2.

Figure.1. Nonparametric regression curve of the spline with small lambda.

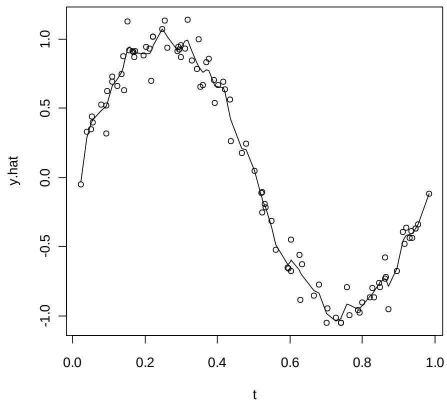
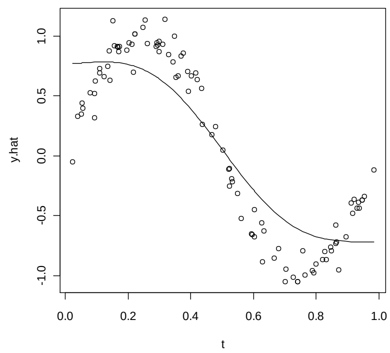


Figure.2. Nonparametric regression curve of the spline with large lambda.



There are several methods to select the smoothing parameter λ. In this study, the GCV method will be used. This method is formulated by replacing the value $a_{kk}(\lambda)$ by

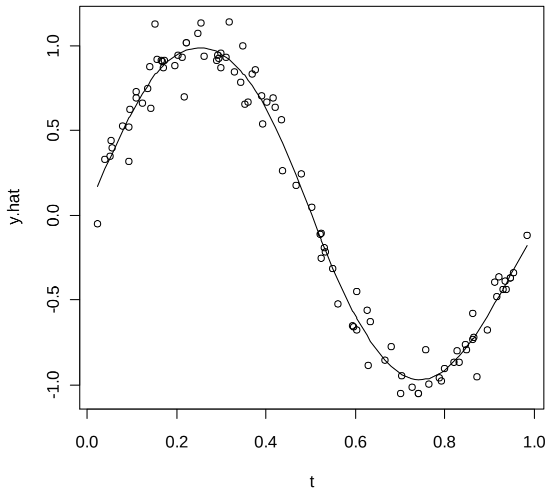
$$\overline{a_\lambda} = \frac{1}{n}\sum_{i=1}^{n} a_{ii} = \frac{1}{n} tr(A_\lambda) \tag{6}$$

Thus, the GCV function is defined with

$$GCV(\lambda) = n^{-1}\sum_{i=1}^{n}\left(\frac{y_i - f(t_i)}{1-\overline{a_\lambda}}\right)^2 = \frac{\frac{1}{n}\left\|I - A_\lambda \underline{y}\right\|^2}{\left[\frac{1}{n} tr(I - A_\lambda)\right]^2} \tag{7}$$

The GCV method has several advantages over GCV. First, the GCV method is easier to calculate, and second, the GCV method has theoretical properties that cannot be proved by the CV method, even though the two methods give close results.

Figure.3. Nonparametric regression curve with optimal smoothing parameters.



and then we entered the variables into the GAM model **by Hastie and Tibshirani (1986, 1990).**

$$\text{grdp=s(labor)+s(expenditures)+s(phone)+s(human)} \tag{8}$$

where

s(.): smooth function

GAMs are additive models that convert each predictor variable to a smooth function by spline, a polynomial function defined by subintervals (piecewise polynomial). Interval boundary points (knots) connect defined polynomials in one continuous function. We ran our GAM model on R software with a GAM library **by Hastie (2020)**. GAM models can be combined with linearity tests for more precise specification.

5. Research Result

5.1. Scatter Plot Data

Scatter plots reveal linearity or nonlinearity among variables. The relation between GRDP and predictor variables is generally but not exclusively nonlinear (Figure 4-Figure7).

Figure.4. Scatter plotting of GRDP and labor variable (X_1).

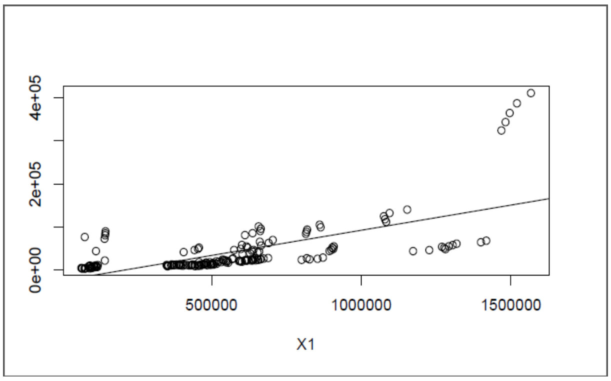


Figure.5. Scatter plotting of GRDP and exp variable (X_2).

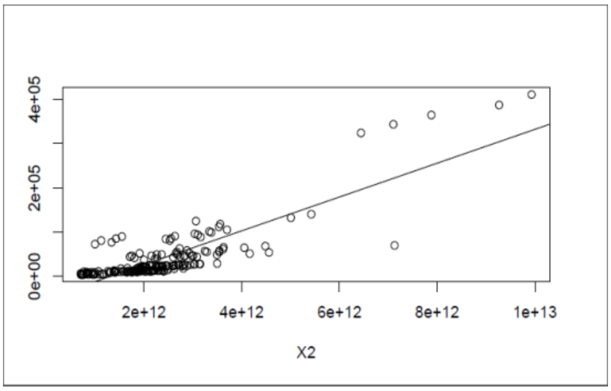


Figure.6. Scatter plotting of GRDP and phone variable (X_3)

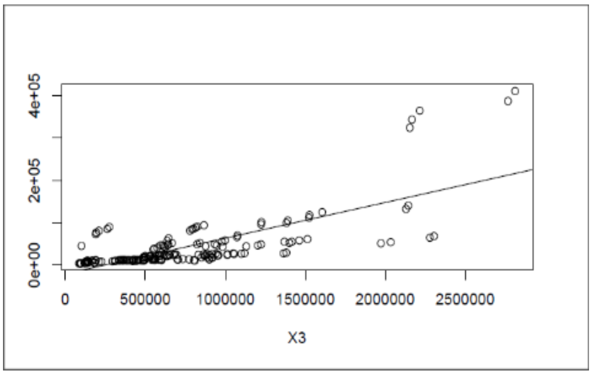
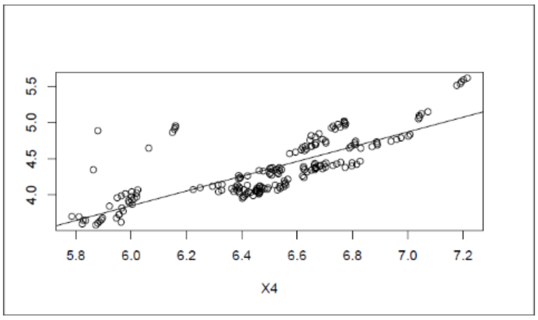


Figure.7. Scatter plotting of GRDP and human variable (X_4).



Based on Figure 4, it can be seen that the variable GRDP and the variable labor have a visual linear relationship because the distribution of the observation data is on a linear line. Based on Figure 5, it can be seen that the variable GRDP and the variable exp have a visual linear relationship because the distribution of the observation data is in a linear line. Based on Figure 6, it can be seen that the variable GRDP and the variable phone have a visual linear relationship because the distribution of the observation data is in a linear line. Based on Figure 7, it can be seen that variable GRDP and variable human have a visual linear relationship because the distribution of observation data is a linear line.

5.2. Correlation Result

Correlations between GRDP and labor, expenditur, mobile-phone, human capital are positive and significant at 95% confidence (Table 2). The P-value of 0.001 ($< \alpha = 0.05$) rejects H_0.

Table.2. Correlation Result**.**

Parameter 1	Parameter 2	r	Confidence Interval 95%	P-value
GRDP	labor	0.65	[0.56; 0.73]	0.001
GRDP	exp	0.84	[0.80; 0.88]	0.001
GRDP	phone	0.73	[0.65; 0.79]	0.001
GRDP	human	0.82	[0.76; 0.86]	0.001

Based on the correlation test performed, it can be seen that the relationship between the GRDP and the predictor variables, including labor, government spending, cell phone users, and human capital, all have a positive relationship with the value of the correlation coefficient. This shows that the GRDP in East Java Province is directly related to all predictor variables whether in East Java Province labor force, government expenditure, cell phone users, and human capital have increased, the GRDP in East Java also increased, and vice versa. Also, it can be seen that the P-value is 0.001 $<\alpha = 0.05$, which means reject H_0. There is therefore a relationship between the variable GRDP and the predictor variables of labor, public expenditure, cell phone users, and human capital.

5.3. Linearity Test

P-values in each model ($< \alpha = 0.05$) indicate nonlinearity between response and predictor variables (Table 3). Specification errors will arise in linear models.

Table.3. Results of Ramsey Testing**.**

Model	Reset Test	df1	df2	P-value
Model labor	65,097	2	186	2.2e-16
Model exp	42,386	2	186	6.799e-16
Model phone	47,911	2	186	2.2e-16
Model human capital	189.73	2	186	2.2e-16

Based on Table 3, it can be seen that the P-value in each model yields $< \alpha = 0.05$, which means rejecting H_0. So, there is a specification error of the resulting linear model or there is no linear relationship between the predictor variable and the response variable.

5.4. GAM Model

Our GAM model (Figure 8) reveals a Gaussian distribution of responses linked by identity function. Its coefficient of determination is 93.6%. We refer to additive models as GAMs even though Gaussian response models often are called additive models instead of GAM models. The difficulty with spline function is to set appropriate smoothing parameters by minimizing generalized cross-validation (GCV). (See **Horowitz (2014)**) for spline in additive econometric models. The optimal parameter is indicated by a GCV score of 2.7297e+08. In our model, GCV corresponds to effective degrees of freedom (edf), of 7.589 for labor, 5.960 for expenditures, 1 for number of cellular phone users, and 7.324 for human capital. The edf value reveals variation in the effect of predictor variables on the response variable. The size of the labor force (number of cellular phone users) generates the most (least) varied effect on GRDP. Significance testing shows that labor, government expenditures, and human capital exert significant nonlinear effects on GRDP. The effect of the number of cellular phone users on GRDP is statistically insignificant.

Figure.8. R software output for the generalized additive model.

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Link function: identity

Formula:

Y ~ s(labor) + s(exp) + s(phone) + s(human)

Parametric coefficients:

            Estimate Std. Error t value Pr(>|t|)

(Intercept)    39603       1124   35.23   <2e-16 ***

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Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:

         edf    Ref.df     F p-value

s(labor) 7.589  8.344  4.101 0.00013 ***

s(exp)   5.960  7.192  2.666 0.01146 *

s(phone) 1.000  1.000  0.409 0.52327

s(human) 7.324  8.138 18.347 < 2e-16 ***

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Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.936   Deviance explained = 94.3%

GCV = 2.7297e+08  Scale est. = 2.4011e+08  n = 190
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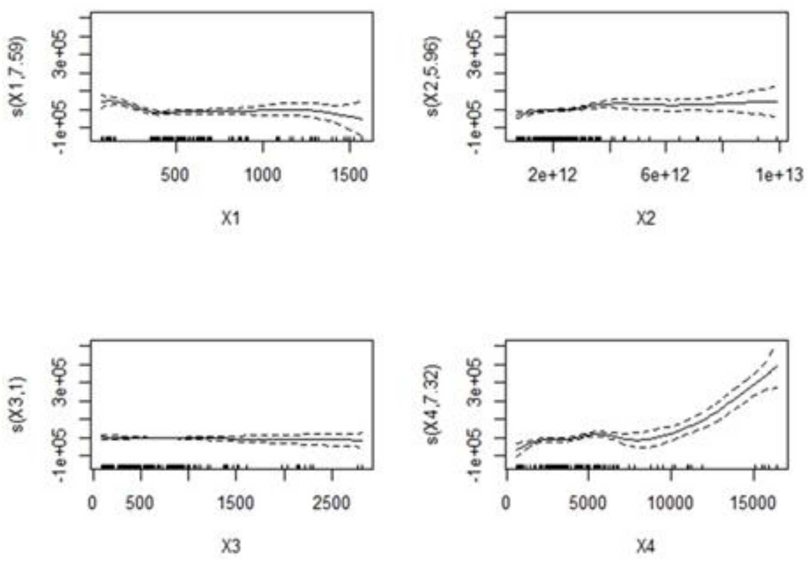
The magnitude of the influence of predictor variables appears via fitted penalized spline for each predictor variable. Plots (Figure 9) for all GAM outputs use the same vertical scale, allowing for a quick comparison of effects. Human capital exhibits the largest effect, with the size of the labor force and local government expenditures increasing steadily. The number of cellular phone users appears to exhibit negligible effects.

Figure.9. Components of smoothing functions for the generalized additive model fit to GRDP.



6. Conclusion

This study has examined how ICT, proxied by the number of cellular phone users, influenced the GRDP of East Java during 2014–2019 using a GAM model. Significance testing shows that the size of the labor force, local government expenditures, cellular phone users, and human capital have a significant nonlinear effect on GRDP. The GAM model revealed that the most (least) varied effect of predictor variables on GRDP is the size of the labor force (cellular phone users). The effect of cellular phone users on GRDP is not significant. Human capital has the largest effect with the size of the labor force and local government expenditures increasing steadily with this predictor. Again, the number of cellular phone users exhibits negligible effects. Although the effect of cellular phone users on GRDP lacks significance, its linear correlation is significant, indicating the model should consider it to examine how technology affects GRDP.

This finding must be considered by governments, business, and society (Purnama and Mitomo, 2018). Central Bureau of Statistics (BPS) indicates that East Java's ICT sector grew by 9.77% during the first quarter of 2020 versus by 6.4% for that quarter of 2019. Gross regional domestic product (GRDP) for the ICT sector reached IDR 28.204 trillion, which was IDR 25,155 trillion above the first quarter of 2019. Therefore, Indonesia's government must continue to develop Internet services by increasing the speed of Internet access and encouraging the use of the public Internet to encourage people's productive activities, which, in turn, can increase income as a contribution to GRDP

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