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# Boosting GDP through Technology: Exploring the Impact of Digital Inclusion in Indonesia

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ABSTRACT: This research examines the influence of digital inclusion on Indonesia's GDP growth from 2017 to 2022. The study utilizes quantitative panel data analysis, enabling an in-depth investigation of the impact of mobile phone ownership and internet access on GDP, using data sourced from the Indonesian Central Bureau of Statistics (BPS) and other sources. The findings reveal that increased mobile phone ownership significantly enhances GDP, underscoring the role of communication technology in driving economic growth. However, while internet access is essential, it does not impact substantially GDP during the studied period, indicating areas for potential improvement in infrastructure and digital literacy.

**Keywords:** Digital Inclusion, GDP Growth, Panel Data, Mobile Technology, Internet Access



## INTRODUCTION

Digital technology has been vital to economic growth in various countries, including Indonesia, over the past few years. Digital inclusion, which encompasses broader access to technologies like mobile phones and the internet, has shown significant potential to boost Gross Domestic Product (GDP) by fostering connectivity, enhancing productivity, expanding markets, and creating innovations (World Economic Forum, 2024).

Studies conducted in various countries indicate increased access to information and communication technologies (ICT), such as mobile phones and the Internet, positively correlates with GDP growth. For instance, a study by Haftu (2019) in Sub-Saharan Africa found that the increased penetration of mobile phones significantly boosted GDP per capita in the region. This suggests expanding access to mobile technologies can help alleviate poverty and improve people's quality of life by driving higher per capita income.

Similarly, various studies acknowledge the importance of digital inclusion in the Indonesian context. Mei and Cheng (2024) emphasize that digital inclusion in Indonesia is crucial for reducing the digital divide and accelerating economic growth, particularly in regions historically lacking access to technology. Access to the internet and mobile phones allows more people to participate in the digital economy, which drives GDP growth (Mei & Cheng, 2024).

Other findings by Novianti and Asmara (2023) also found that advancements in digital technology have positively impacted Indonesia's economic growth. Additionally, investment, road infrastructure length, education index, and labor force participation rate contribute positively to economic development in Indonesia. In contrast, the variable for open unemployment harms the country's economic growth.

In this study, we explore a unique aspect of digital inclusion by distinguishing between the effects of mobile phone ownership and internet access on Indonesia's economic growth. While many previous studies emphasize the broad impact of digital inclusion, our findings reveal a critical differentiation: mobile phone ownership significantly positively influences GDP, whereas internet access. This distinction offers new insights into how different digital technology components contribute to economic development. It highlights the need to investigate why internet access has not yet fully realized its potential to drive economic growth in Indonesia. Focusing on this nuance, our study aims to deepen the understanding of digital technology's role in boosting GDP, providing valuable context for future policy and infrastructure development.

This research aims to evaluate the impact of digital inclusion on Indonesia's GDP growth from 2017 to 2022. It highlights independent variables such as the rate of mobile phone ownership among the population and the number of people who have accessed the internet within the last three months, while the dependent variable is GDP at constant prices. The data is expected to provide empirical evidence, offer deeper insights into the influence of digital technology on Indonesia's economic growth, and help identify policies and infrastructure that can optimize the benefits of digital inclusion.

## Digital Inclusion

Digital inclusion refers to the ability of individuals and groups to access, use, and benefit from digital technology, including the Internet and devices like computers and mobile phones. As technology evolves rapidly, digital inclusion has become increasingly important and vital to the economy, education, and social life.

Digital inclusion is a condition where everyone has what they need to participate in, contribute to, and benefit from the digital world. It's not only about having access to the internet and digital technologies but also about possessing the necessary digital skills, motivation, and confidence to utilize these technologies effectively (Hartnett, 2019).

Digital technologies significantly impact education, particularly in supporting inclusive education. Digital technologies can help reduce educational disparities by providing broader access to learning resources and materials. Additionally, digital tools allow more personalized and adaptive learning to support students with diverse needs. However, the digital divide continues to impede access, especially for vulnerable groups, including students with disabilities (Lütgen, 2019).

Furthermore, digital inclusion is critical to enhancing financial stability by broadening access to digital financial services. This enables individuals and businesses across various economic levels to participate in a more comprehensive financial system, reducing reliance on traditional methods and improving transaction efficiency. Through digital inclusion, previously unbanked communities now access services like online payments, microloans, and digital savings, all of which contribute to more excellent financial stability (Lütgen, 2019).

In Indonesia, the digitization of financial services has enhanced financial inclusion and improved banks' operational efficiency by reducing financial intermediation costs. However, despite the various advantages of digital finance, challenges such as low digital literacy and unequal access to technology must still be addressed to ensure that all segments of society fully benefit from this development (Widarwati et al., 2022).

While digital inclusion offers numerous benefits, significant challenges hinder achieving social equity in the digital realm. One major challenge is the "digital divide," which often exacerbates existing inequalities, particularly in developing countries where access, quality of use, affordability, and digital skills vary greatly. Additionally, measurement shortcomings and inadequate policies pose barriers to bridging the digital divide and achieving social equity through digital inclusion (Sharp, 2022).

**Endogenous Growth Theory**

Endogenous Growth Theory is an economic theory that attributes economic growth to internal factors, such as investment in research and development (R&D), education, and technological innovation, rather than relying solely on external or exogenous factors like increases in labor or capital accumulation. This theory emphasizes the role of knowledge, innovation, and government policies in driving long-term economic growth (Romer, 1990).

In his research, Jones (2021) analyzed the impact of non-rivalry of ideas on economic growth through semi-endogenous growth theory. Jones (2021) found that increasing levels of education and global research intensity have driven economic growth in the United States over recent decades. However, he also noted that future growth might slow without innovations and significant contributions from technologies like artificial intelligence that could further stimulate economic growth.

Thach's (2021) research examines the application of endogenous growth theory in developing economies known as NEST (Potential Emerging and Growth-Leading Economies). The study found that countries successfully developing endogenous growth tend to experience significant increases in economic output and R&D investment. The research highlights that adopting technology and innovation plays a crucial role in driving sustainable economic development in NEST countries, with solid R&D serving as a primary driver in accelerating productivity and innovation.

This theory also highlights the importance of spillover effects, where knowledge and innovations created by one company can benefit others. Human capital, generated through education and training, also plays a vital role in this theory, as more excellent knowledge and skills can enhance an economy's capacity for innovation.

Research by Barcenilla-Visús, López-Pueyo, & Sanaú-Villarroya (2014) demonstrates that increasing an economy's ability to absorb technology through improved human capital can accelerate economic growth, particularly in technology-dependent manufacturing sectors (Barcenilla-Visús et al., 2014).

Economic policies that encourage innovation and education are crucial in facilitating endogenous growth. Howitt (2004), in his progress report on endogenous growth theory, emphasizes that policies supporting technology transfer, improving public infrastructure, and fostering competition can enhance productivity growth and innovation in the economy (Jones, 2021).

Capolupo (2008) discusses how technology, seen as an endogenous factor in growth theory, can be directly influenced by economic policy decisions and investments in R&D. This contrasts with exogenous growth theories, which view technology as an external factor beyond control (Capolupo, 2008).

## Gross Domestic Product (GDP)

Gross Domestic Product (GDP) is a primary economic indicator used to measure the total value of goods and services produced within a country over a specific period, typically one year. GDP encompasses several key components that reflect a country's economic activity (Barro et al., 1990).

GDP includes critical components such as household consumption, investment, government expenditure, and net exports (exports minus imports). Household consumption usually represents the largest share of GDP, reflecting individual and household purchases of goods and services. Investment includes purchases of capital goods like machinery, equipment, and infrastructure development that support long-term economic growth. Government expenditure includes all government spending on goods and services, such as education, health, and defense. Finally, net exports represent the difference between exports and imports, where a trade surplus boosts GDP while a trade deficit reduces it. Research shows that increases in these components, particularly consumption and investment, can significantly contribute to overall GDP growth (Tampubolon et al., 2023).

## Nominal vs. Real GDP

Nominal GDP is calculated using current market prices without adjusting for inflation or price changes. As a result, nominal GDP reflects increases due to inflation rather than actual increases in production. In contrast, Real GDP adjusts the GDP value for inflation, providing a more accurate picture of a country's economic growth. Actual GDP measures changes in the volume of goods and services produced over time, using constant prices from a selected base year to eliminate the effects of inflation.

In economic literature, such as Mankiw (2010) and Barro et al. (1990), Nominal GDP is often used to provide a quick overview of the overall economic value. Real GDP is more advantageous for a deeper analysis of actual economic growth. Acemoglu (2009) also emphasizes the importance of using Real GDP in long-term economic growth analysis, as it allows for more accurate comparisons between different periods without distorting price fluctuations. Therefore, understanding the difference between Nominal and Real GDP is essential in economic analysis to avoid misinterpreting economic growth.

## METHOD

This study adopts a quantitative approach with panel data analysis to evaluate the impact of digital inclusion on Gross Domestic Product (GDP) growth in Indonesia during the period 2017-2022. Quantitative research focuses on numerical measurement and variable analysis to generate data that can be generalized to a broader population through representative samples (Mohajan, 2020). This method was chosen because panel data analysis allows for exploring the influence of independent variables on dependent variables while accounting for both temporal and spatial variations across provinces in Indonesia. This approach provides more comprehensive and accurate results in understanding the dynamics involved.

The study utilizes secondary data from the Central Bureau of Statistics (BPS), the Ministry of Home Affairs (Kemendagri), Finaka, Jayani, and Opendata Kalbar. The data includes the number of mobile phone owners and people who accessed the internet in the last three months as independent variables and Indonesia's GDP at constant prices as the dependent variable.

The research employs three analytical models: Fixed Effects Model (FEM), Random Effects Model (REM), and Pooled OLS Model. A series of statistical tests were conducted to determine the most appropriate model, including the Chow test, the Hausman test, and the Breusch-Pagan Lagrangian Multiplier (LM) test. The Chow test compares the Pooled OLS Model with the Fixed Effects Model, while the Hausman test helps to choose between the Random Effects Model and the Fixed Effects Model. The Breusch-Pagan Lagrangian Multiplier test is applied to determine whether the Random Effects Model is more suitable than the Pooled OLS Model Baltagi (2021).

Multicollinearity and heteroscedasticity tests were conducted to ensure the validity of the analysis results. The multicollinearity test aims to detect any high correlation between independent variables that could distort the interpretation of regression results. To address this issue, variable standardization was carried out by converting the variable values into z-scores, ensuring that all variables are on the same scale. The heteroscedasticity test was also performed using the Modified Wald test, which ensures that the error variance across groups in the regression model remains consistent and unbiased (Cui et al., 2023). With this methodology, the study is expected to produce valid and reproducible results for researchers interested in conducting similar studies on the impact of digital inclusion on economic growth in Indonesia.

## RESULT AND DISCUSSION

### Breusch-Pagan Lagrangian Multiplier (LM) Test

```
. xttest0

Breusch and Pagan Lagrangian multiplier test for random effects

        pdb[id,t] = Xb + u[id] + e[id,t]

        Estimated results:
                         |       Var     SD = sqrt(Var)
                ---------+-----------------------------
                     pdb |   3.33e+29       5.77e+14
                       e |   7.01e+28       2.65e+14
                       u |          0              0

        Test: Var(u) = 0
                             chibar2(01) =     0.00
                          Prob > chibar2 =   1.0000
```

Figure 1: Breusch-Pagan Lagrangian Multiplier (LM) Test (Source: Processed data)

The model shows that the variable "hp" (the number of mobile phone owners) has a significant negative coefficient on Indonesia's GDP, meaning that an increase in mobile phone users is associated with a decrease in GDP. On the other hand, the variable "internet" (the number of people accessing the internet) has a significant positive coefficient, indicating that increased internet access is positively correlated with GDP growth. However, it is essential to note that both within-group and between-group variance are zero, meaning the model can explain no variation across or within groups.

The Breusch-Pagan Lagrangian Multiplier (LM) test results show an extremely high probability value (1.0000), indicating insufficient evidence to support using a random effects model over the pooled OLS model. This suggests that the random effects model does not perform better than a model that assumes the data from all groups can be pooled without accounting for panel structure (pooled OLS). This result is further supported by a rho (ϱ) value of zero, indicating no variance explained by group differences (u_i), thus suggesting that the pooled OLS model may be more appropriate for this analysis (Abdullah et al., 2023).

### Chow Test

```
. xtreg pdb hp internet, fe

Fixed-effects (within) regression               Number of obs     =         18
Group variable: id                              Number of groups  =          3

R-squared:                                      Obs per group:
     Within  = 0.8389                                         min =          6
     Between =      .                                         avg =        6.0
     Overall = 0.0158                                         max =          6

                                                F(2, 13)          =      33.85
corr(u_i, Xb) = -0.9905                         Prob > F          =     0.0000

------------------------------------------------------------------------------
         pdb | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
          hp |   8.77e+07   3.97e+07     2.21   0.046      2009269    1.73e+08
    internet |   -3911034   1.14e+07    -0.34   0.737    -2.85e+07    2.07e+07
       _cons |   1.14e+15   3.53e+15     0.32   0.753    -6.50e+15    8.77e+15
-------------+----------------------------------------------------------------
     sigma_u |  4.541e+15
     sigma_e |  2.648e+14
         rho |  .99661095   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(2, 13) = 6.16                       Prob > F = 0.0131
```

Figure 2: Chow Test (Source: Processed data)

The pooled OLS regression results show that the variable "hp" significantly negatively affects GDP, while "internet" has a significant positive effect. However, when switching to the fixed effects model, the coefficient for "hp" becomes positive and vital, while the impact of the "internet" variable becomes insignificant. This demonstrates substantial differences in coefficient estimates when individual group effects (id) are considered, indicating that significant between-group variations influence the estimation results.

A specific test is required to compare the two models to determine the most appropriate model between pooled OLS and fixed effects. The Chow test (or F test in the fixed effects model) was performed for this. In the fixed effects model, the F test resulted in a significant p-value (Prob > F = 0.0131), meaning that we reject the null hypothesis that all individual effects (u_i) are equal to zero. In other words, the fixed effects model is more appropriate than the pooled OLS model, as personal effects across groups are essential and must be accounted for. In this case, the Chow test supports using the fixed effects model, pointing to significant heterogeneity between groups that affect the relationship between the independent and dependent variables (Binkley & Young, 2022).

### Hausman Test

```
. hausman fe re

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |       fe           re         Difference       Std. err.
-------------+----------------------------------------------------------------
          hp |   8.77e+07    -2.02e+07        1.08e+08        3.94e+07
    internet |   -3911034     2.42e+07       -2.81e+07        1.06e+07
------------------------------------------------------------------------------
                          b = Consistent under H0 and Ha; obtained from xtreg.
           B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

    chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            =   7.06
Prob > chi2 = 0.0294
(V_b-V_B is not positive definite)
```

Figure 3: Hausman Test (Source: Processed data)

The Hausman test produced a chi-square value of 7.06 with a p-value of 0.0294. This p-value, less than 0.05, indicates a significant difference between the coefficient estimates in the fixed effects and random effects models. Therefore, we reject the null hypothesis (that the difference in coefficients between the two models is not systematic), suggesting that the random effects model is inconsistent and that the fixed effects model is more suitable for this analysis.

Furthermore, in the fixed effects model, the coefficient for the variable "hp" shows a significant positive effect on GDP, while the coefficient for the "internet" variable is insignificant. In contrast, the random effects model shows notably different coefficients, particularly for the variable "hp," which significantly negatively affects GDP. This significant difference supports the results of the Hausman test, which recommends using the fixed effects model, as it provides more consistent estimates when there is a correlation between individual effects (id) and the independent variables (Le Gallo & Sénégas, 2023).

### Model Selection

Based on the results of the Breusch-Pagan Lagrangian Multiplier (LM), Hausman, and Chow tests, the Fixed Effects model is the most appropriate choice. The Breusch-Pagan Lagrangian Multiplier (LM) test shows an extremely high probability (1.0000), indicating insufficient evidence to support using the Random Effects model over the Pooled OLS model. This implies that the Random Effects model does not perform better than the Pooled OLS model, which combines data from all groups without considering the panel structure.

Furthermore, the Hausman test results, with a p-value of 0.0294 (less than 0.05), indicate a significant difference between the coefficient estimates in the Fixed Effects and Random Effects models. This suggests that the Random Effects model does not provide consistent estimates, making the Fixed Effects model more suitable, especially when there is a correlation between individual effects and the independent variables.

Additionally, the significant Chow test (Prob > F = 0.0131) further supports using the Fixed Effects model. This test shows that individual effects (id) cannot be ignored, and the Fixed Effects model allows for capturing relevant variations between groups that affect the dependent variable. While the LM test indicates that Random Effects is no better than Pooled OLS, combining the Hausman and Chow test results provides strong evidence that the Fixed Effects model is the best option for panel data analysis.

**Multicollinearity Test**

The multicollinearity test is used in regression analysis to detect high correlations between independent variables in the model. Multicollinearity occurs when independent variables are significantly correlated, which can cause problems in interpreting regression results. The presence of multicollinearity makes some variables that should be significant and statistically insignificant, obscuring the relationship between independent and dependent variables. Multicollinearity can be detected using several techniques, such as correlation coefficients and the Variance Inflation Factor (VIF). When multicollinearity is detected, several approaches can address it, including reducing insignificant independent variables or using advanced regression methods like ridge regression or principal component analysis (Shrestha, 2020).

```
. vif, uncentered
```

| Variable | VIF | 1/VIF |
|---|---|---|
| hp | 26.97 | 0.037084 |
| internet | 26.97 | 0.037084 |
| Mean VIF | 26.97 | |

Figure 4: VIF Multicollinearity Test Result (Source: Processed data)

The VIF analysis results in the figure indicate that the variables "hp" and "internet" have identical VIF values of 26.97. This suggests a very high level of multicollinearity between the two variables. Such multicollinearity can make it challenging to interpret regression results because the independent variable coefficients may not be accurately estimated, and their standard errors may increase, reducing the model's reliability for prediction and inference.

Standardizing variables is one approach to addressing multicollinearity in regression analysis. Standardization involves converting independent variables to the same scale, typically by subtracting the mean of each variable and dividing by its standard deviation. This process can reduce the correlation between independent variables, which often causes multicollinearity. Research has shown that standardizing variables can improve the stability of estimates in regression models, particularly in linear regression contexts where multicollinearity is a significant issue

(Mamouei et al., 2022). Standardization helps minimize the influence of large-scale variables and avoids estimation bias that may arise from scale differences between variables (Allam et al., 2020).

```
. egen std_hp = std(hp)
(225 missing values generated)

.
. egen std_internet = std(internet)
(225 missing values generated)
```

Figure 5: Standardizing Variables for Multicollinearity Test (Source: Processed data)

The commands `egen std_hp = std(hp)` and `egen std_internet = std(internet)` in Stata are used to standardize the variables "hp" and "internet." This standardization process converts the original values of these variables into standard scores (z-scores). With standardization, the values of the "hp" and "internet" variables are transformed so that their distribution has a mean of zero and a standard deviation of one. This is done to make the two variables comparable in analysis, especially when they have different scales or units

```
. vif, uncentered

    Variable |       VIF       1/VIF
-------------+------------------------
      std_hp |      5.55    0.180178
std_internet |      5.55    0.180178
-------------+------------------------
    Mean VIF |      5.55
```

.Figure 6: Multicollinearity Test Results After Variable Standardization (Source: Processed data)

After standardization, the interpretation of the Variance Inflation Factor (VIF) values shows that both variables have VIF values of 5.55. VIF values below ten are generally considered to indicate no serious multicollinearity issues, but values close to or above five still indicate a reasonably strong correlation between the independent variables. In this case, a VIF value of 5.55 suggests that although standardization has been applied, there is still a moderate correlation between the "std_hp" and "std_internet" variables, though not at a concerning level.

### Heteroscedasticity Test

```
. xttest3

Modified Wald test for groupwise heteroskedasticity
in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (3)  =        2.12
Prob>chi2 =      0.5482
```

Figure 7: Heteroscedasticity Tes (Source: Processed data)

Based on the Modified Wald test results to detect heteroscedasticity across groups in the fixed effects regression model, the chi-square value is 2.12, with a probability (Prob > chi2) of 0.5482. Since this probability value is much larger than the significance threshold of 0.05, we do not have sufficient evidence to reject the null hypothesis that there is no heteroscedasticity (homoscedasticity) between groups. Therefore, it can be concluded that the model used satisfies the homoscedasticity assumption, indicating no evidence of heteroscedasticity in this model.

The Modified Wald test ensures that the model used has consistent error variance across groups, a fundamental assumption in panel data analysis. Further research indicates that this type of Wald test can also be adjusted for various heteroscedasticity conditions, including those involving interactive variables in fixed-effects panel data models (Cui et al., 2023). Adjusting the Wald test helps provide more accurate and robust estimates of heteroscedasticity issues, ultimately improving the validity of conclusions drawn from the regression model.

### Panel Data Regression Using Fixed Effects

```
. xtreg pdb std_hp std_internet, fe

Fixed-effects (within) regression               Number of obs     =         18
Group variable: id                              Number of groups  =          3

R-squared:                                      Obs per group:
     Within  = 0.8389                                         min =          6
     Between =      .                                         avg =        6.0
     Overall = 0.0158                                         max =          6

                                                F(2, 13)          =      33.85
corr(u_i, Xb) = -0.9905                         Prob > F          =     0.0000

------------------------------------------------------------------------------
         pdb | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      std_hp |   4.01e+15   1.81e+15     2.21   0.046     9.19e+13    7.93e+15
std_internet |  -1.79e+14   5.23e+14    -0.34   0.737    -1.31e+15    9.50e+14
       _cons |   1.08e+16   6.24e+13   173.16   0.000     1.07e+16    1.09e+16
-------------+----------------------------------------------------------------
     sigma_u |  4.541e+15
     sigma_e |  2.648e+14
         rho |  .99661095   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(2, 13) = 6.16                       Prob > F = 0.0131
```

Figure 8: Panel Data Regression Using Fixed Effects (Source: Processed data)

Based on the regression results from the Fixed Effects test displayed, this model shows that the variable "std_hp" has a significant positive impact on GDP, with a coefficient of 4.01e+15 and a p-value of 0.046. This indicates that, after controlling for other variables, an increase in the standard deviation of mobile phone users (hp) is significantly associated with an increase in Indonesia's GDP. In contrast, the variable "std_internet" has a negative coefficient of -1.79e+14. However, it is statistically insignificant with a p-value of 0.737, indicating that in this model, changes in internet access do not have a sufficiently significant impact on GDP.

The coefficient of determination (R-squared within) in this model is 0.8389, suggesting that approximately 83.89% of the variability in GDP within groups can be explained by variations in the independent variables included in this model. A rho value of 0.9966 indicates that most of the variability in GDP is due to between-individual (id) differences, supporting the use of the Fixed Effects model. The F-test indicates that the model is overall significant with a p-value of 0.0000, meaning that this model effectively explains the variability in GDP.

The findings of this research align with the Endogenous Growth Theory, which emphasizes that economic growth is driven by internal factors such as technological innovation, education, and investment in human capital. According to Romer (1990), technology and innovation play a central role in fostering long-term economic growth, directly contributing to productivity gains.

In the context of this study, the positive impact of mobile phone ownership on Indonesia's GDP growth is consistent with the principles of endogenous growth theory. The proliferation of mobile phones can be seen as an innovation that enhances communication, access to information, and overall productivity across various sectors of the economy. This aligns with Thach's (2021) findings, where technology adoption drives sustainable growth in developing economies by increasing productivity and innovation.

Moreover, this study's spillover effects—another critical aspect of endogenous growth theory—are evident. The increasing number of mobile phone users creates knowledge spillovers, enabling businesses to leverage communication technology for efficiency improvements. This supports the idea that investments in technology yield widespread benefits beyond the initial adopters, fostering economic growth across multiple sectors.

However, the finding that internet access does not significantly impact GDP during the studied period suggests there are limitations in digital infrastructure or digital literacy in Indonesia, preventing internet access from fully contributing to economic growth. This is consistent with Howitt's (2004) assertion that economic policies must support technology infrastructure to achieve long-term growth. The underutilization of internet access could indicate inadequate investment in digital infrastructure, which remains a barrier to maximizing the benefits of technology for the economy. Thus, the findings of this study provide empirical support for the endogenous growth theory, emphasizing the role of mobile phone penetration in driving economic growth while highlighting areas for improvement in internet infrastructure to unlock growth potential further.

In conclusion, the Fixed Effects model demonstrates that the number of mobile phone users has a significant positive impact on GDP, while internet access does not show a significant effect. This model is suitable for the panel data, especially as it accounts for between-group (id) variation and explains a substantial portion of GDP variability.

## CONCLUSION

This study highlights the significant impact of digital inclusion, particularly mobile phone ownership, on Indonesia's GDP growth from 2017 to 2022. The Fixed Effects model reveals that an increase in mobile phone users correlates positively with GDP, highlighting the critical role of communication technology in expanding access to information, improving efficiency, and boosting productivity across sectors. However, the effect of internet access on GDP has been less pronounced, likely due to limitations in infrastructure and digital literacy. While internet access can drive future growth, infrastructure and access quality improvements are needed to realize its economic benefits fully.

The policy implications of these findings suggest the need for a greater focus on developing telecommunications infrastructure, particularly in increasing mobile phone access and penetration to drive Indonesia's GDP growth. The government may consider expanding mobile phone service coverage to underserved areas and promoting programs that encourage using this technology in daily economic activities. This can boost economic participation by connecting more people to markets, services, and opportunities, thus improving productivity across various sectors.

Additionally, initiatives to increase mobile phone adoption, such as affordable devices or incentives for mobile-based business services, can help integrate communication technology into daily economic activities, further driving growth. Moreover, despite the limited impact of internet access so far, the government should focus on improving digital literacy programs and broadband infrastructure to maximize the potential of internet-based technologies in the future. By fostering a more connected population, communication technologies can effectively reduce barriers to economic participation, enhance overall GDP growth, strengthen digital inclusion, and support more sustainable and inclusive economic growth.

This study's limitations include using two main variables, mobile phone ownership, and internet access, without accounting for other factors that may also influence GDP growth. For instance, variables such as investment in technology infrastructure (e.g., fiber-optic networks or 5G development), digital literacy levels (which determine how effectively the population can use available technologies), and government support for technology adoption (in terms of policies or incentives) could provide a more comprehensive understanding of the role of digital inclusion. Moreover, the study is limited to a relatively short period, which may not capture the long-term effects of digital inclusion on economic growth, especially as infrastructure improvements or digital literacy efforts typically take longer to show substantial results.

For future research, it is recommended to extend the study over a longer period and consider additional variables that may provide more comprehensive insights into the relationship between digital inclusion and economic growth. Further research could also explore the impact of digital literacy, the adoption of technology by specific economic sectors, and the role of government policies in accelerating digital inclusion. This would provide more in-depth guidance for shaping effective policies that harness digital technology to promote sustainable economic growth in Indonesia. The findings of this research are expected to assist the government and other stakeholders in designing more targeted strategies to ensure that the benefits of digital technology are fully optimized for national economic advancement.

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