JURNAL RISET ILMU EKONOMI
www.jrie.feb.unpas.ac.id
ISSN 2776-4567

Unravelling Income Inequality in Indonesia: A Machine Learning Approach to Understanding The Impact Of Information and Communication Technology

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DOI doi.org/10.23969/jrie.v3i2.63
Citation Al Azies, H., & Herowati, W. (2023). Unravelling Income Inequality in Indonesia: A Machine Learning Approach to Understanding The Impact Of Information and Communication Technology. Jurnal Riset Ilmu Ekonomi, 3(2), 89–100. https://doi.org/10.23969/jrie.v3i2.63

ABSTRACT

This study aims to analyze the effect of Information and Communication Technology (ICT) on income inequality in Indonesia. The analytical method used includes linear regression to evaluate the causal relationship between the dependent variable (Gini Ratio) and ICT indicators. Furthermore, the k-means clustering algorithm is used to group provinces based on ICT characteristics. The results of the regression analysis show that the ICT variables have a significant influence on the Gini Ratio, illustrating the close relationship between ICT and income inequality. In addition, clustering produces two regional groups: Cluster 1, with better access and use of ICT, and Cluster 2, with lower ICT characteristics but advantages in telecommunication infrastructure. This research shows the importance of inclusive and sustainable ICT development to reduce income inequality in Indonesia. Appropriate policies for increasing the accessibility and use of ICTs can have a positive impact on social and economic development throughout Indonesia.

Keywords: : Information and Communication Technology, Income Gap, Machine Learning, Linear Regression, K-means Clustering

INTRODUCTION

Information and communication technology (ICT) has had an impact on many facets of Indonesian life, including the economy (Jahanger & Usman, 2022). The growth of ICT opens up new possibilities for the digital economy, makes it easier to access information, and boosts productivity across a range of industries (Jahanger & Usman, 2022; Rostiana et al., 2022; Rostiana & Djulius, 2019; Yousefi, 2011). Behind this promising promise, though, there are worries that the growth of ICT can potentially widen the wealth disparity (Demir et al., 2022). In Indonesia, where income levels range significantly between different classes of people, income inequality is a big problem. The Gini Ratio, sometimes known as the Gini Coefficient, is a popular indicator for measuring income inequality (Furman et al., 2019; Liu & Gastwirth, 2020). The Gini Ratio is a measure of economic inequality that ranges from 0 to 1, with 0 indicating ideal income distribution (everyone has the same income) and 1 indicating extremely high inequality (everyone has all income) (Liu & Gastwirth, 2020).

Understanding the infrastructure economy in developing countries, such as Indonesia, reveals that infrastructure, which includes electricity, transportation, telecommunications, water, and sanitation, plays a critical role (Straub, 2008). According to the most recent study survey, infrastructure is not only a supporting element, but also the primary engine of economic growth, at the national, regional, and sectoral levels (Straub, 2008). Currently, in the Indonesian environment, emphasis is being placed on ICT infrastructure. ICT has the potential to be the key to economic growth, delivering huge digital economic prospects and improving productivity in a variety of industries. A comprehensive and in-depth analytical methodology is required to better comprehend the influence of ICT expansion on income disparity in Indonesia, as well as how ICT has impacted the economic infrastructure in various provinces. As a result, in this study, we use two major machine learning algorithms, namely regression and clustering. In this work, regression (supervised learning) and clustering (unsupervised learning), two machine learning algorithm methods (Dalal, 2020), are used to more fully comprehend the impact of ICT on the degree of income disparity in Indonesia.

This study will employ secondary data and surveys to investigate the causal association between ICT-related variables and the Gini Ratio using the regression approach. The regression method will assist in identifying ICT characteristics that significantly influence the degree of income disparity in distinct Indonesian regions or populations. As a result, this study will aid in determining how ICT advancements may influence alterations in the Gini Ratio as a whole. Meanwhile, this study will employ the clustering method to aggregate ICT data from various provinces in Indonesia based on key ICT variables. The clustering method will aid in the identification of provincial groups that share comparable ICT features. The clustering results can provide insight into the distribution of ICT development in Indonesia, as well as if there are developing patterns in the use and acceptance of ICT in different regions. The originality of this study lies in the fact that it combines these two approaches to offer a more comprehensive and in-depth perspective on how ICT affects the income disparity among Indonesians. With this method, it may be possible to find hidden connections between ICTs and income disparity as well as gain a richer, more in-depth understanding of the numerous elements influencing income inequality at the local and national levels. Similar research that examines the impact of ICT on income disparity, such as the following studies, has not discovered this (Che Arshad & Irijanto, 2023; Djulius et al., 2022; Faizah et al., 2021; Patria & Erumban, 2020; Suharno et al., 2022; Untari et al., 2019).

METHODS

Data Sources and Research Variables

The Statistics Indonesia (BPS), which provided the data for this study, in 2021. The Gini Ratio serves as the analysis' dependent variable. The independent variables are attempting to predict or explain this variable. Table 1 below lists the independent variables used in this analysis.

Table 1. ICT infrastructure variables (The Independent Variables)

Variable	Literature
Access Index and ICT infrastructure	(Fuady, 2019)
ICT Usage Index	(Fuady, 2019)
Number of villages that have BTS towers with strong telephone signal reception	(Putra, 2019)
Number of villages that have BTS towers with weak telephone signal reception	(Putra, 2019)
Number of villages that have BTS towers with no telephone signal reception	(Putra, 2019)
Percentage of Population Aged 5 and Over Who Has Accessed the Internet	(Wajuba et al., 2021)
Number of villages that have internet facilities at village offices	(Wajuba et al., 2021)
Access Index and ICT infrastructure	(Putri & Sumardi, 2023)

Source: The Statistics Indonesia

Methods of Analysis and Research Flow

This study uses machine learning algorithm methods, namely regression and clustering, to analyze the effect of ICT on the Gap of Public Income in Indonesia. One statistical technique for examining the causal linkages between one or more independent variables (in this case, the ICT indicator) and one dependent variable (the Gini Ratio) is linear regression (Manik et al., 2023; Maulud & Mohsin Abdulazeez, 2020; Setiawan et al., 2021; Taloba et al., 2022). The independent variable in this study takes the shape of several ICT indicators that wish to evaluate their impact on the Gini Ratio, whilst the dependent variable, the Gini Ratio, is the variable that wants to be predicted or explained. The use of linear regression will aid in determining the significance of each ICT indicator's influence on the level of income inequality in Indonesia, as assessed by the Gini Ratio. The linear regression analysis will yield a regression coefficient, which indicates the size of the independent variable's (the ICT indicator's) influence on the dependent variable (the Gini Ratio) (Song et al., 2022). Furthermore, these coefficients indicate whether the relationship between these variables is positive (directly proportional) or negative (inversely proportional). Significant linear regression analysis results can provide insight into which ICT indicators have a strong influence on income inequality in Indonesia, assisting the government and policymakers in developing strategies and policies that are more effective in reducing income inequality and increasing inclusive and equitable utilization of Information and Communication Technology throughout Indonesia. The model used in this study is as follows:

$$\boldsymbol{Y = \beta_0 + \beta_1 Access + \beta_2 Usage + \beta_3 BTSA + \beta_4 BTSB + \beta_5 BTSC + \beta_6 Int + \beta_7 Fac} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \mathbf{(1)}$$

Y	= The Gini Ratio
β	= Estimator coefficient
Access	= Access Index and ICT Infrastructure
Usage	= ICT Usage Index
BTSA	= Many villages have BTS towers with strong telephone signal reception.
BTSB	= Many villages have BTS towers with weak telephone signal reception.
BTSC	= Many Villages Have BTS Towers with No Telephone Signal Reception.
Int	= % of the Population Aged 5 and Over Who Have Accessed the Internet
Fac	= Many Villages Have Internet Facilities at Village offices.

This study employed the clustering approach, namely k-means (Sinaga & Yang, 2020), after performing linear regression analysis to classify provinces in Indonesia based on ICT characteristics as reflected by ICT indices. K-means is a machine learning clustering algorithm that seeks to divide data into many clusters based on similar qualities or attributes (Azies & Rositawati, 2021; Monica et al., 2021). The independent variables in this study are ICT indicators such as the ICT access and infrastructure index, the ICT use index, the proportion of the population who has used the internet, and others. The k-means approach divides Indonesian provinces into numerous groupings (clusters) based on the similarity of ICT features indicated by ICT indices (Widjanarko Otok et al., 2022). As a result, this clustering will aid in understanding the pattern of distribution of ICT usage in Indonesian regions, as well as identifying regional groups with comparable levels of ICT availability and use. This grouping can provide significant insights into developing policies and strategies to improve the use of ICT in all Indonesian provinces. Furthermore, information on the features of ICT in each cluster can help policymakers build programs that are more in line with the needs and potential of each regional group to expand ICT use and close technology gaps in Indonesia.

RESULT

It is anticipated that the income disparity in a region will narrow as ICT development becomes more sophisticated. The Gini coefficient is a measure of the degree of income inequality generally. The Gini Coefficient has a value between 0 and 1.

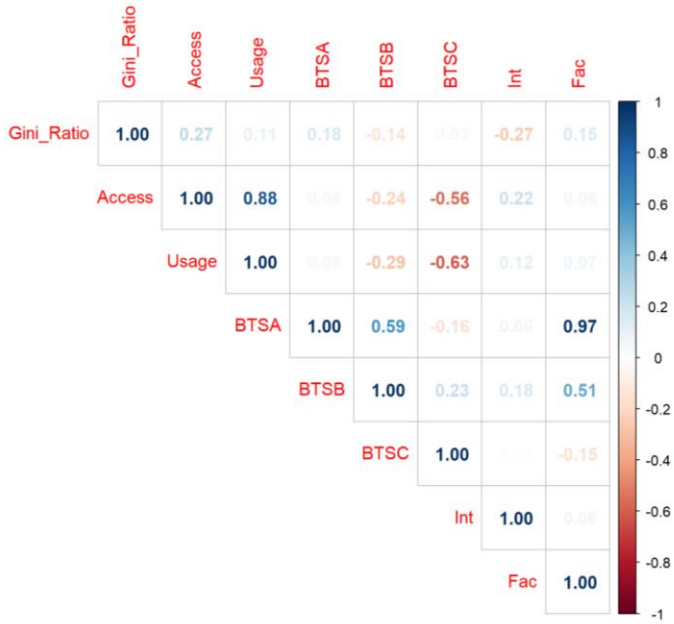

Figure 1. Plot of the relationship between ICT infrastructure variables and income disparity

If the Gini Coefficient is 0, then there is complete income equality, or it means that everyone makes the same amount of money(Furman et al., 2019). A correlation analysis was first performed to ascertain the relationship between the variables employed in this study (Emerson, 2015). Correlation analysis is carried out to determine the strength of the linear relationship between the dependent variable (Gini Ratio) and the independent variables (Access, Usage, BTSA, BTSB, BTSC, Int, and Fac), which are ICT indicators in Indonesia. The results of the correlation study show that there are different levels of relationship between these variables (Figure 1). The Gini Ratio has a sluggishly positive connection with both Access (0.27) and Usage (0.11), indicating that the Gini Ratio tends to be greater the more access and use there is of ICT. The Gini Ratio and Int have a moderately negative association (-0.27), indicating that the Gini Ratio tends to be lower the more internet access there is in the population. The Gini Ratio exhibits a sluggishly positive connection with both BTSA (0.18) and Fac (0.15), indicating that the Gini Ratio tends to be higher in villages with more ICT infrastructure amenities, such as BTS towers with good signal reception or internet access at village offices. The Gini Ratio and BTSB have a weak negative association (-0.14), meaning that the Gini Ratio tends to be lower in more villages with BTS Tower facilities that have poor phone signal reception. The Gini Ratio and BTSC have a correlation that is almost negligible (0.03), indicating that there is little to no linear relationship between these variables. The correlation analysis in this study provides a first description of the relationship between the variables. It is crucial to note, however, that correlation does not imply causation, and these findings are merely a first step towards further analysis, such as linear regression, to better understand the impact of these variables on the Gini Ratio in Indonesia. In addition, linear regression analysis and clustering were used to investigate and find more complicated patterns in the research data. Following the completion of the correlation analysis, the next phase in this study is modeling with a linear regression algorithm. Linear regression is a statistical approach for modeling a linear relationship between the dependent and independent variables, which is an indicator of ICT in Indonesia.

DISCUSSION

All independent variables in the results of the analysis above (Tabel 2) except *Fac* (Number of Villages with Internet Facilities at Village Offices). have p-values that are less than the level of significance. indicating that they significantly affect the Gini Ratio in Indonesia. Number of Villages with Internet Facilities at Village Offices does not have a significant impact at the designated level of significance (5%=0.05) while having a p-value that is higher than the level of significance. The coefficient. which is a number in the outcomes of this linear regression analysis. indicates how much of an impact each ICT indicator (*Access* to *Fac*) has on Indonesia's Gini Ratio level. A positive coefficient means that the ICT indicator and Gini Ratio are positively correlated. which means that the likelihood of income inequality is higher than the ICT indicator value. In contrast. the negative coefficient exhibits a negative association with the Gini Ratio indicating that the likelihood of income inequality is reduced the greater the value of the ICT indicator.

Table 2. Modelling the Influence of ICT Infrastructure Variables on Income Disparity Using the Linear Regression Algorithm

Variable	Coefficient	Std. Error	t value	P-value	Significance
Intercept	2.69	1.003	2.68	0.01252	-
Access	0.05782	0.017	3.45	0.00192	Significant
Usage	-0.03122	0.015	-2.09	0.04693	Significant
BTSA	0.00005	0.000	2.26	0.03278	Significant
BTSB	-0.00034	0.000	-2.46	0.02107	Significant
BTSC	0.00444	0.002	2.24	0.03394	Significant
Int	-0.02561	0.010	-2.47	0.02032	Significant
Fac	-0.00002	0.000	-1.61	0.12015	Not significant

Source: Data Processed by Researchers

The ICT Access and Infrastructure Index variable has the highest coefficient value in the findings of the analysis above. with a value of 0.05782. This demonstrates that the Gini Ratio in Indonesia is most influenced by the ICT Access and Infrastructure Index. According to the interpretation of the positive coefficient value (0.05782). there is a greater likelihood of income disparity in a region with a higher ICT Access and Infrastructure Index value. This may imply that due to some factors affecting wealth distribution. places with superior ICT infrastructure may tend to have a wider income difference. The findings of this investigation shed light on how income disparity in Indonesia is impacted by ICT indicators. Several factors, including the ICT Access and Infrastructure Index, the ICT Usage Index, the number of villages with strong telephone signal reception, the number of villages with weak telephone signal reception, the number of villages with no telephone signal reception, and the percentage of the population who have accessed the internet, have a significant impact on the Gini Ratio and can be taken into account when formulating policies aimed at reducing income disparities and increasing equity.

The next phase in this research is to apply a different machine learning technique, namely the clustering algorithm, after receiving the findings from the linear regression modeling. An approach for unsupervised learning called clustering divides data into several groups or clusters based on their shared traits. K-means is the clustering algorithm employed in this investigation. Data are grouped into k clusters, where k is the specified number of clusters, to run the k-means algorithm(Monica et al., 2021; Sinaga & Yang, 2020). K-means is used to locate the cluster center (centroid) to minimize the distance between the data and the matching cluster center. The values of the ICT indicators (Access, Usage, BTSA, BTSB, BTSC, Int, and Fac) in each Indonesian province were utilized as the data for clustering. Based on the similarity of the ICT indicator values owned by each province, the k-means algorithm will cluster these provinces.

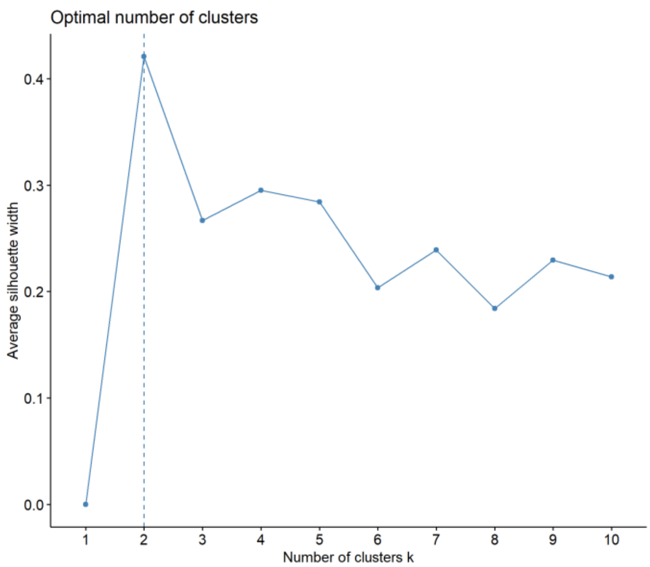

Figure 2. Silhouette index plot for determining the optimal number of clusters

The silhouette approach or the silhouette index can be used to choose the greatest number of clusters when the k-means clustering algorithm is applied (Widjanarko Otok et al., 2022). In comparison to other clusters, the silhouette index calculates how closely each object in a specific cluster matches that cluster. The silhouette index ranges from -1 to 1, and a positive value means the object is in the right cluster while a negative value means it is in a different cluster. The quality of the cluster division improves with a larger silhouette index value. The ideal number of clusters is two, as illustrated by the experimental outcomes using the silhouette index approach in Figure 2. This demonstrates that based on the similarity of ICT features owned by each province, the classification of Indonesia's provinces into two groups or clusters may be made. Based on the high silhouette index value, which shows that the objects in the cluster have a high degree of similarity within their groups and a notable distinction from other groups, clustering with these two clusters yields the best representation. The following Figure 3 displays the clustering's findings: 26 provinces make up Cluster 1, while the final nine provinces make up Cluster 2.

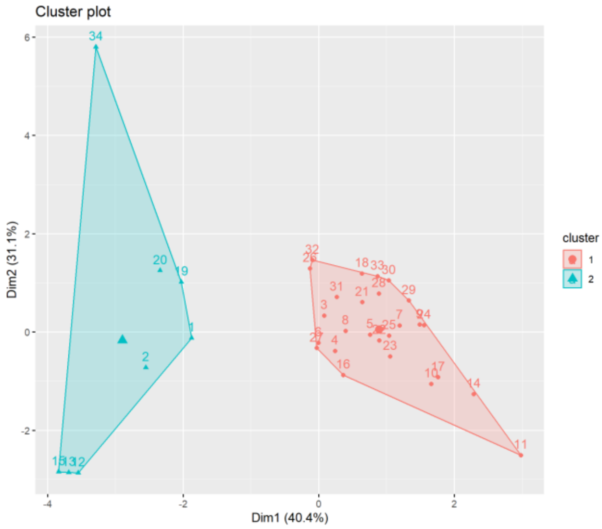

Figure 3. Cluster Plot for optimal number of clusters k=2

Based on the clustering results, regions in Indonesia are divided into two clusters. The following is a list of provinces included in each cluster:

Table 3. Cluster Members Based on Optimal Clustering Results

Cluster 1	Cluster 2
West Sumatra, Riau, Jambi, South Sumatra, Bengkulu, Lampung, Kep. Bangka Belitung, Kep. Riau, DKI Jakarta, D.I. Yogyakarta, Banten, Bali, West Nusa Tenggara, Central Kalimantan, South Kalimantan, East Kalimantan, North Kalimantan, North Sulawesi, Central Sulawesi, South Sulawesi, Southeast Sulawesi, Gorontalo, West Sulawesi, Maluku, North Maluku, West Papua	Aceh, North Sumatra, West Java, Central Java, East Java, East Nusa Tenggara, West Kalimantan, Papua

Source: Data Processed by Researchers

Two clusters that describe the various information and communication technology (ICT)-related features of areas in Indonesia were produced by the clustering technique used in this study (Table 3). 26 provinces that can access and use ICT more easily makeup Cluster 1. These provinces exhibit strong levels of infrastructural access and ICT usage, and more communities now have access to telephones and the Internet. The proportion of residents in this cluster who have used the internet is likewise quite high. Contrarily, Cluster 2 is made up of nine provinces with less suitable ICT features than Cluster 1. However, Cluster 2 has an advantage in terms of the proportion of settlements that receive strong telephone signals. Almost on par with Cluster 1, Cluster 2 exhibits a very high level of internet access among its populace. The clustering results paint a clearer picture of the distribution and variations in ICT use in Indonesia. Regions in Cluster 1 are those that are prepared for economic growth backed by sound ICT infrastructure and active ICT use (Table 4).

Table 4. ICT Characteristics of Each Cluster (Average Score)

Indicator	Cluster 1	Cluster 2
Access	6,11	5,65
Usage	5,57	4,84
BTSA	631,38	2437,50
BTSB	64,54	176,00
BTSC	1,00	4,25
Int	98,60	98,72
Fac	815,31	3820,75

Source: Data Processed by Researchers

To attract investment and generate jobs, the economic growth potential of this cluster can be maximized by creating larger digital technologies and services. In the meanwhile, Cluster 2 has promise for a more robust communications infrastructure, particularly in terms of solid phone signal coverage. To increase the population's quality of life and engagement in the digital economy, effort must be taken to ensure that the regions in this cluster do not fall behind in more active ICT use and utilization.

CONCLUSION

According to this study, information and communication technology (ICT) has a major impact on economic disparity in Indonesia. The regression study results demonstrate a substantial link between the ICT variable and the Gini ratio, which is a measure of income inequality. In this setting, ICT has a significant influence in altering income distribution across Indonesia. Furthermore, using clustering analysis, this study identifies two regional groupings with distinct ICT features. Cluster 1 has better ICT access and use, whereas Cluster 2 has lower ICT features but superior telecom infrastructure. These findings illustrate the range of ICT applications in Indonesia's various regions. The findings of this study have significant consequences. Governments and stakeholders can build more inclusive policies by analyzing the relationship between ICT and economic inequality and identifying geographical groupings with different ICT features. In Indonesia, implementing inclusive ICT policies can assist in reducing income disparity and enhance sustainable development. As a result, this research lays a solid foundation for policy actions targeted at improving economic equality in the country.

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