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Modeling Indonesia's regional economic growth for sustainable development planning

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ABSTRACT

This study aims to evaluate Indonesia's regional economic performance using gross regional domestic product (GRDP) per capita at the provincial level from 2015 to 2021. Utilizing business intelligence technology through Tableau, the study integrates descriptive, predictive, and prescriptive analytics to examine interregional GRDP dynamics. The k-means clustering method is employed to classify provinces into three clusters based on economic similarity. The results reveal a persistent economic disparity between the western and eastern regions of Indonesia, with provinces such as DKI Jakarta and East Kalimantan grouped in the high GRDP cluster, while East Nusa Tenggara and Papua fall into the lowest cluster. Trendline and forecasting analyses provide projections of economic growth through 2030, indicating that some provinces demonstrate stable upward trends, whereas others show stagnation or declining patterns. Based on these findings, this research offers data-driven policy recommendations aimed at promoting more equitable and sustainable economic development across Indonesia.

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1. INTRODUCTION

Economic growth in Indonesia's regions is one of the key factors that influence the creation of new jobs, industrialization process, exports, and investments [1]. Among all the different industries, the manufacturing sector is one of the leading factors behind economic activity since it creates very strong connections with transport, trade, energy, logistics, and services, which contributes to a dynamic economy in the region [2]. However, economic performance varies significantly between different regions of Indonesia. Western regions show better results in terms of economic performance since there is a greater contribution from manufacturing industries, while eastern regions are based on agricultural and mining industries [3]. In previous research conducted in the regional economy of Indonesia, researchers used the descriptive approach of statistics to analyze the contribution of different sectors to the economy and also to find the interdependence among various macroeconomic variables, such as gross regional domestic product (GRDP), employment rate, inflation rate, poverty, and income level [4], [5]. Even though this study helped understand about the regional economy in depth, these researchers were mostly concerned with describing past events and did not provide much help in terms of future planning and policy formulation. In addition, there are studies on aggregate economic indicators that lack a thorough sectoral study that could help in analyzing the strengths and weaknesses of each industry in each province [6]. It is thus possible that such critical aspects of regions as well as differences between provinces will not be captured effectively by the current methodologies of regional economic studies. The inadequacies of the current methodologies underscore the importance of a more holistic approach that can both describe the economic structure of a region and predict future trends as well.

The progress of artificial intelligence, machine learning, big data analytics, and business intelligence technologies has helped in analyzing economies and making policies [7], [8]. Business intelligence tools like Tableau help analyze amounts of economic data and share findings with stakeholders [9]. These tools help in understanding the economy and communicating the results to people involved. The use of techniques helps in finding similarities and differences among provinces based on their economic characteristics. Forecasting methods support in predicting regional trends [10].

In spite of all these advances, there is still a gap in literature concerning the development of a framework for an integrated approach to descriptive, predictive, and prescriptive analyses in the regional economy of Indonesia. The current literature review shows that the synergistic use of artificial intelligence, machine learning, and business intelligence has been hardly ever used for providing assistance in economic planning and decision-making. The current study is concentrated on the economic aspect of sustainable development. The GRDP per capita will be used as the measure of economic success of a region. It is obvious that economic growth is crucial for creating job opportunities and equalizing differences between regions while improving social welfare of population. Nevertheless, the current study does not intend to evaluate the level of sustainability comprehensively. On the contrary, it is supposed to contribute to achieving sustainable development goals (SDGs) 8 and 10, which are related to the promotion of decent work and economic growth and reduction of inequalities [11].

The economy of Indonesia is analyzed through an integration of analytical tools, which include predictive and prescriptive analytics. The use of descriptive analytics is applied in analyzing the economic structure of each province, determining differences between sectors and also the impact of manufacturing sector on the economy [12]. Researchers used analytics to guess what the economy will be like in the future and to see how things like investments, the number of people working, and the number of factories will affect the economy [13]. As part of prescriptive analytics in this study, evidence-based recommendations will be suggested for purposes of ensuring inclusive economic growth and decreasing disparities among regions in the Indonesian provinces. Considering that the major focus of this study is the economy of the national and provincial levels of Indonesia, the recommended solutions would be used by policymakers in order to enhance economic development of the region [14]. Prescriptive analytics gives us ideas that are based on facts to help make sure everyone has a chance to grow economically and to reduce the differences between regions.

The new thing about this study is that it uses different methods to plan for the economy, like grouping similar things together, predicting what will happen, and using pictures to show data with Tableau. This study is different from ones that just looked at numbers and described them. Instead, it uses a look at the economy, predicts what will happen, and uses pictures to show data so that we can come to conclusions that make sense. The plan that is suggested mainly helps the economy be more sustainable by making regions more productive, helping industries grow, and reducing the differences between provinces. Prescriptive analytics helps us make decisions, and prescriptive analytics is very important for economic development.

2. METHOD

The dataset used in this study is presented social, economic, and demographic indicators at the provincial level and was obtained from Kaggle [15] and Badan Pusat Statistik (BPS) [16]. Data preprocessing: this initial stage prepares raw data for analysis and includes following processes are [17], [18], included: importing data files (CSV/Excel), data cleaning (removing duplicates and handling missing values), data transformation (normalization and encoding), and data integration when sourced from multiple datasets. Data storage and distribution: following preprocessing, the data are stored in a database or integrated system containing several key attributes [19], such as province geographic region, year in which the data were recorded, GRDP employed, and GRDP capita. Data analysis: this is the core analytical phase of the study, utilizing several techniques: k-means clustering (groups provinces according to similarities in economic indicators), trendline analysis (identifies temporal patterns and long-term data trajectories), and forecasting (predicts future GRDP values based on historical trends). In the current research work, the Euclidean distance is calculated as (1) and (2).

$$d(x, c) = \sqrt{(\sum_{i=1}^{n} (x_i - c_i)^2)} \quad (1)$$

$$c_j = (1/|S_j|) \sum_{x} \in S_j\, x \quad (2)$$

The forecasting model used was the autoregressive integrated moving average (ARIMA) to forecast future GRDP trends from past patterns. The reason for choosing the ARIMA forecasting model is because it performs well in forecasting economic time series with trends. The mathematical form of the ARIMA forecasting model is defined as (3).

$$Y_t = c + \sum_{i=1}^{p} \varphi_i Y_{t-i} + \sum_{j=1}{}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \quad (3)$$

Forecasting performance was assessed using the root mean square error (RMSE) and mean absolute percentage error (MAPE). RMSE quantifies the average prediction error magnitude, whereas MAPE assesses forecasting accuracy based on percentages. The formulas for the assessment are defined in (4) and (5).

$$RMSE = \sqrt{((1/n) \sum_{i=1}^{n} (y_i - \hat{y}_i)^2)} \quad (4)$$

$$MAPE = (100\%/n) \sum_{i=1}^{n} |(y_i - \hat{y}_i)/y_i| \quad (5)$$

The current research develops a framework referred to as the regional development intelligence framework (RDIF). Unlike the traditional approach that is mainly focused on descriptive analysis, the developed framework combines descriptive, clustering [20], predictive, visual, and prescriptive analysis into one decision-making framework. The RDIF turns regional economic data into intelligence that helps identify differences and understand patterns of development [21]. As a partitioning clustering method, each data instance must be assigned to exactly one cluster. Moreover, the method allows data points to shift between clusters during iterative updates when their proximity to the cluster centroids changes throughout the optimization process.

The first stage is descriptive analytics, which makes use of GRDP per capita as the main economic performance measure. Economic structure analysis is done in order to determine the economic structure as well as the foundation for further analysis. Clustering analytics is the second step that aims at identifying the economic archetypes and classifying the provinces into homogeneous clusters according to their economic performance levels.

In turn, predictive analytics can then be employed for examining the time dynamics in economics using trendlines and forecasting, whereby the provinces can be classified into growth, stagnation, or decay categories. The visual analytics, using Tableau business intelligence, creates interactive dashboards which allow for data integration, analysis, and interpretation, thus improving the transparency of decision-making. Lastly, prescriptive analytics creates cluster-based policy decisions based on the collective findings from the three types of analysis. The main benefit of RDIF is the combination of economic profiling, archetyping, prediction, visualization, and policy recommendations within one analytical environment, which can convert regional economic information into development intelligence for regional planning.

3. RESULTS AND DISCUSSION

3.1. Descriptive analytics: economic profiling and industry analysis

This is the initial phase where we analyze using descriptive analytics to have an in-depth knowledge of the economic status of the region. In this analysis, GRDP per capita and industry contribution will be analyzed to determine the nature of the economy in each of the regions. This phase allows us to evaluate the structure and industry composition of the economy.

Based on the GRDP per capita data presented for all Indonesian provinces, a substantial economic disparity across regions is clearly evident. DKI Jakarta records the highest GRDP per capita at IDR 1,136,026.27 thousand (approximately IDR 1.13 billion per capita per year), reflecting its position as the national center of economic, financial, and governmental activity. This result is expected given the dominance of the services, finance, and technology sectors, as well as the high levels of investment concentrated in the capital city. In contrast, provinces such as East Kalimantan, Riau Islands, and North Kalimantan also report high GRDP per capita values, primarily driven by the mining industry, energy production, and natural resource–based exports.

Conversely, eastern Indonesian provinces such as East Nusa Tenggara, Maluku, and North Maluku display considerably lower GRDP per capita levels, with East Nusa Tenggara ranking the lowest at IDR 85,509.27 thousand. This indicates limitations in infrastructure access, low levels of industrialization, and minimal high-value economic activities in these areas. Such disparities also highlight uneven patterns of investment distribution and development across Indonesia. Therefore, these figures not only reflect the economic performance of each province but also serve as critical indicators for formulating more equitable and sustainable development policies. From the point of view of information and communication technology

(ICT), this research project underscores the significance of combining economic data at a regional level with interoperable government information systems, specifically those controlled by BPS and the Indonesian Ministry of Finance. While the dataset in question was sourced from Kaggle, the methodological approach to the research stresses the significance of ensuring compliance with government open data standards for enhanced reliability and transparency. Application of tools for business intelligence such as Tableau ensures effective data integration, automated visualization, and design of dashboards that can be used for e-governance purposes and tracking of intelligent public policies.

3.2. Cluster analysis: discovery of economic archetypes

The second step utilizes cluster analysis in order to divide the provinces into clusters according to the similarity in their economic traits. The purpose of clustering is not simply to sort the provinces in terms of numerical parameters, but rather to discover the economic archetypes that demonstrate various states of prosperity and development trajectories. Following the clustering process, an analysis was conducted to interpret the characteristics of each cluster, including the identification of provinces with high, medium, and low GRDP per capita. Additional visualizations using cluster-based color differentiation were applied to further clarify intergroup distinctions. This process aims to provide a deeper understanding of economic inequality across Indonesian regions and to establish an analytical basis for developing more targeted policy recommendations. Based on Figure 1, the clustering results based on the variable sum of GRDP per capita at the provincial level yield three distinct groups that clearly reflect the degree of average economic prosperity per individual in each province. Cluster 1, consisting of 28 provinces, represents the largest group and includes most regions in Indonesia, such as Central Java, East Java, South Sumatra, and South Sulawesi. Provinces in this cluster exhibit relatively low to moderate average GRDP per capita levels, with a cluster center of approximately 204,870. This indicates that individual economic activity remains within the general national range.

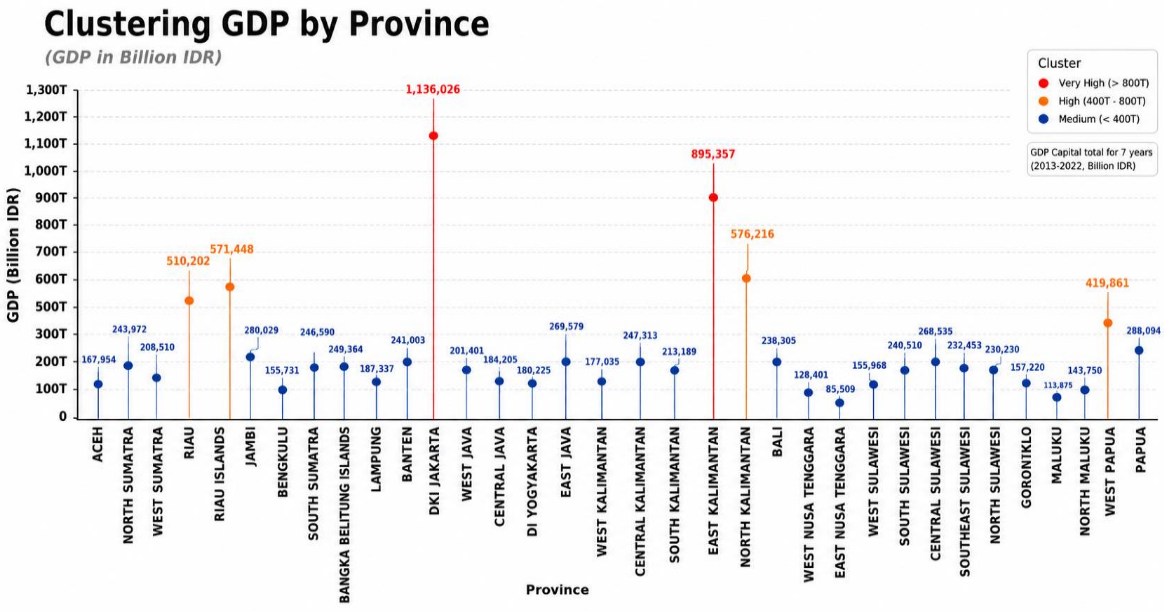

Figure 1. Clustering results of GRDP per capita in Indonesian provinces

Cluster 2 consists of four provinces, North Kalimantan, Riau Islands, West Papua, and Riau—classified as regions with upper-middle GRDP per capita, with a cluster center of approximately IDR 519,430. Although this value is lower than cluster 2, it remains considerably above the national average. These provinces are characterized by economies dominated by natural-resource extraction and processing activities such as mining, oil and gas, and export-oriented industries. Their relatively small populations further contribute to their high GRDP per capita values.

In contrast, cluster 3 comprises only two provinces, DKI Jakarta and East Kalimantan, both of which exhibit exceptionally high GRDP per capita values of 1,136,026.27 and 895,357.16, respectively. With a cluster center of roughly 1,015,700, this group stands far above all other provinces, reflecting significantly higher levels of economic productivity and individual prosperity. As the nation's capital and primary business hub, DKI Jakarta naturally contributes substantial economic output. Similarly, East Kalimantan, driven by extractive industries and serving as the designated location for the new national capital (IKN), generates high economic value relative to its population size, which substantially elevates its per capita GRDP.

3.3. Predictive analytics-trend and forecast analysis

The third phase uses predictive analytics to examine the future path of the economy. Future forecasting and trendline analysis are used to determine the growth trend of provinces over a period of time and any risk involved due to lack of growth or decline. The third phase is more than just a descriptive analysis because it allows us to predict the future trends of regions.

Based on Figure 2, the results of the forecast and trendline analyses for DKI Jakarta and East Kalimantan, the projected trajectories and observed trends consistently reflect the economic conditions in both provinces, although distinct differences emerge in their respective growth patterns. For DKI Jakarta, both the forecast model and the trendline indicate sustained and stable increases in GRDP per capita. Between 2015 and 2021, the actual data show an increase from IDR 142,913 in 2015 to IDR 174,963 in 2021. Forward projections estimate that GRDP per capita will reach approximately IDR 217,620 by 2030, aligning closely with the upward trend depicted in the trendline analysis. Forecast results reinforce this pattern, with prediction intervals suggesting stable growth.

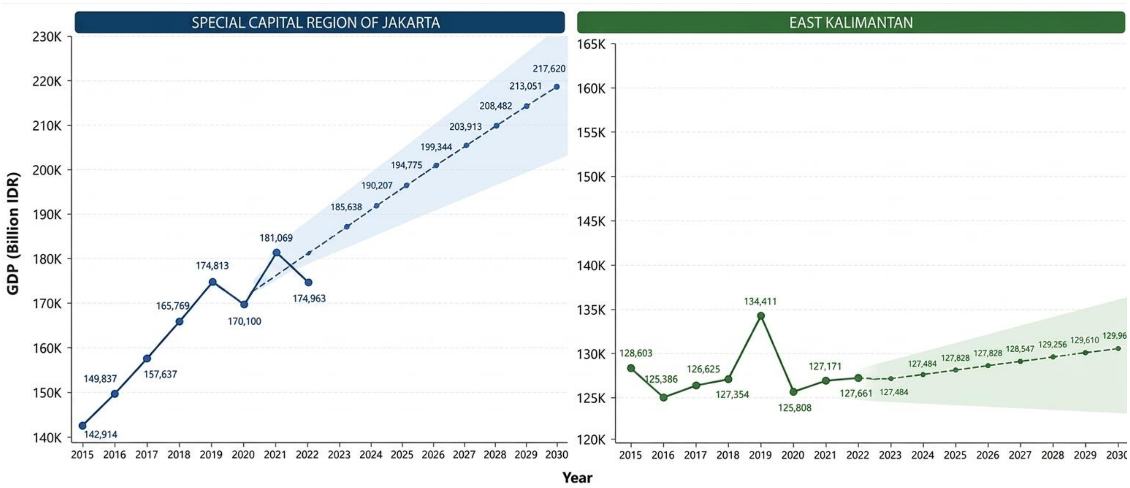

Figure 2. Forecast results and trendline cluster 2

The widening upper and lower bounds reflect the potential for accelerated economic expansion, supported by post-pandemic recovery and government policies that strengthen the service sector, technological innovation, and investment flows. DKI Jakarta and East Kalimantan have shown a divergence in their economic trends and predictions in terms of GDP per capita. There has been steady growth of the economy in DKI Jakarta, due to a thriving service sector and digital economy and finance, among others. Predictions show that DKI Jakarta is set to continue its growth path until 2030.

In contrast, East Kalimantan exhibits very slow and stagnant growth. Both the forecast and trendline analyses show that GRDP per capita in the province remains relatively unchanged, increasing only marginally from IDR 128,603 in 2015 to approximately IDR 128,901 in 2030. Overall, East Kalimantan's GRDP per capita remains substantially lower than that of DKI Jakarta, and its long-term forecast reflects minimal economic momentum. The forecast model produces values nearly identical to those observed in 2021, with narrow prediction intervals that indicate limited drivers of future growth. This stagnation is largely attributable to the province's reliance on extractive industries, which are highly vulnerable to fluctuations in global commodity prices. Although the relocation of the IKN to East Kalimantan has the potential to generate long-term economic benefits, these effects have not yet materialized and are expected to emerge only gradually. On the contrary, East Kalimantan displays a relatively static growth trend. Even though the province is rich in natural resources and strategically located with regard to the national capital development program, the dependency of the region on mining operations makes the economic development inflexible in the long run. The forecast range stays relatively narrow. In terms of ICT and digital transformation, predictive analytics through business intelligence systems such as Tableau could be used to facilitate scenario-based monitoring for regional development. Through forecast dashboards, policymakers could assess the future economic path of their economies, recognize the risks of becoming stagnant, and adopt corresponding fiscal policies.

Based on Figure 3, forecast and trendline analyses for North Kalimantan and West Papua, two markedly different economic growth trajectories are observed. North Kalimantan demonstrates a positive and stable upward trend in GRDP per capita, reflected in both the historical data and future projections. From 2015 to 2021, GRDP per capita increased from IDR 76,823 to IDR 88,510.

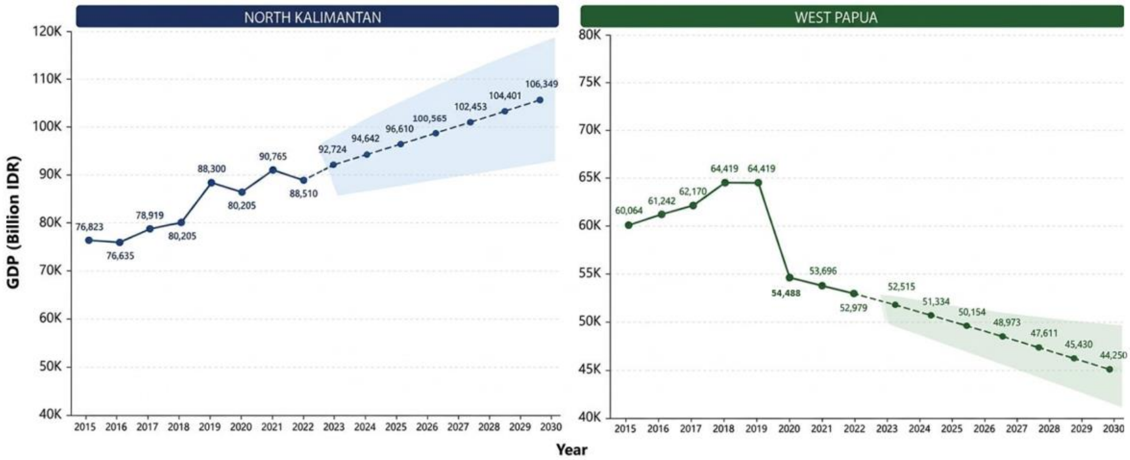

Figure 3. Forecast results and trendline cluster 3

Forward projections indicate continued growth, with estimates reaching approximately IDR 106,348 by 2030. The forecast model is supported by relatively narrow prediction intervals, signifying a high degree of confidence in the projected growth path. This pattern indicates strengthening economic performance, likely driven by gradual expansion in industrial or mining activities, as well as increasing regional economic activity. The disparity in economic trends of North Kalimantan compared to West Papua. The economy of North Kalimantan is experiencing stable economic growth and is projected to continue rising until 2030 due to its growing industrial production. In contrast, West Papua exhibits a concerning downward trajectory. After rising from IDR 60,064 in 2015 to IDR 64,499 in 2018, GRDP per capita began to decline sharply, particularly after 2019. By 2021, the figure had fallen to IDR 52,979, and projections through 2030 indicate a continued decline to approximately IDR 44,249. The lower prediction interval shows an even steeper drop, reaching around IDR 26,135, signaling substantial uncertainty and significant risk of economic contraction. Both the trendline and forecast models confirm a persistent downward trend, which may be attributed to declining performance in key economic sectors, reduced investment, or insufficient economic diversification. Additional contributing factors may include regional development disparities or inadequate infrastructure to support sustained economic growth. In the case of West Papua, however, there exists a persistent decline in its trend, marked by falling GDP per capita and high forecast uncertainty. The possible reasons for this trend include poor performance in industry, lack of diversification, and infrastructure problems. The use of ICT in predictive analysis in this case becomes an important strength that can be enjoyed by local governments. Using dashboard integration and prediction mechanisms through data, the government is able to plan effective strategies to address vulnerability in regions that require attention.

Based on Figure 4, the combined analysis of forecasting and trendline models for the provinces of East Nusa Tenggara and Papua, two contrasting economic growth trajectories in terms of GRDP per capita are evident. East Nusa Tenggara demonstrates a stable and positive growth trend. Since 2015, its GRDP per capita has steadily increased from IDR 11,087 to IDR 13,092 in 2021. Projections for the period 2022 to 2030 indicate a continued upward trend, with estimates reaching approximately IDR 15,801 by 2030. The prediction intervals are relatively narrow, suggesting a high degree of confidence in the accuracy of the forecasts. This stability reflects a consistently developing regional economy, likely driven by growth in the tourism and agricultural sectors [22], as well as sustained and evenly distributed government development programs. The trendline analysis reinforces these findings, displaying a smooth, linear growth pattern that aligns with the positive direction indicated by the forecast results.

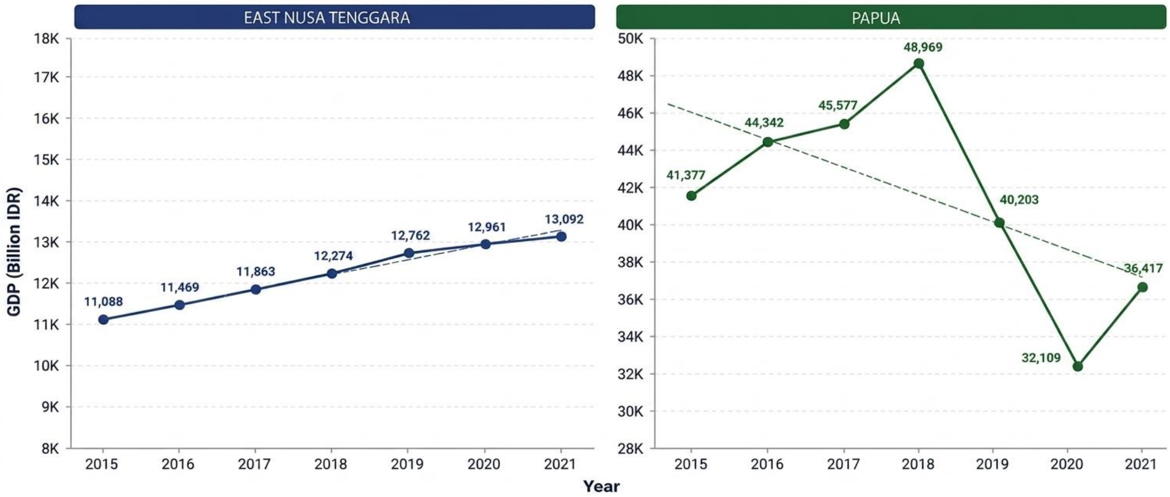

Figure 4. Forecast results and trendline cluster 1

In contrast, Papua exhibits far less stable economic performance. After initially rising from IDR 41,376 in 2015 to IDR 48,069 in 2018, its GRDP per capita experienced a sharp decline, reaching IDR 32,108 in 2020, followed by a modest recovery to IDR 36,416 in 2021. However, forward projections indicate a persistent downward trend, with estimated GRDP per capita declining to approximately IDR 31,614 by 2030. The lower bound of the prediction interval continues to fall under IDR 21,000, highlighting significant uncertainty and substantial economic risk moving forward. This decline may be associated with disruptions in key sectors, such as mining following Freeport's restructuring, the impacts of the COVID-19 pandemic, and recurring socio-political challenges in the region. Moreover, Papua's trendline does not exhibit a clear pattern, indicating highly volatile historical economic performance and increasing forecast uncertainty. Overall, the combined findings from the forecast and trendline analyses not only confirm the presence of economic contraction in Papua but also underscore the structural challenges facing the region and the urgent need for more strategic development interventions.

3.4. Visual analytics: business intelligence and interactive dashboards

In the final stage of the proposed model, visual analytics will be achieved via creation of interactive dashboards using Tableau business intelligence [23]. In this stage, there is provision for incorporation and visualization of regional economic datasets at large scales, and also for presentation of analytical output obtained from descriptive, clustering, and predictive analytics [24]. The interactive dashboard provides a platform for exploration of economic indicators through different dimensions, including regional inequalities, development trends, and time [25]. Moreover, with the help of business intelligence, decision-making process becomes easier since complex analytical output will be converted into intuitive visualizations that can be understood easily [26]. Thus, visual analytics will be an important part of intelligent governance since policymakers will be able to keep track of performance of regional economies, detect any structural inequalities, and development trends among provinces [27].

3.5. Prescriptive analytics: policy suggestions for each cluster

The final stage of the framework utilizes prescriptive analytics in order to derive actionable policy conclusions based on the empirical results of clustering and forecasting analysis [28]. Instead of making recommendations that are applicable to all cases under study, this stage connects the intervention measures to economic performance and development trends of different regions and their projections. Those provinces which show a low or decreasing trend of GRDP per capita [29], such as those found in lower-performing clusters, will need specific policies aimed at economic diversification to lessen their dependence on primary industries and ensure their immunity from external influences. There is a clear empirical basis for the implementation of differentiated policies from the outcome of the clustering exercise. Provinces that fall under the category of having a high GRDP per capita (including DKI Jakarta and East Kalimantan) have strong economic structures based on services and resource endowment, while most of the other provinces falling into the low- and medium-income categories lack diversified industries and have relatively low levels of productivity [30].

The forecast results also reinforce this explanation by demonstrating differences in growth paths among clusters over the long term. Provinces that have diverse economies display either steady or rising GRDP per capita, whereas provinces that are dependent on natural resources display stagnant or highly volatile GRDP per capita. Thus, any policy implications drawn from this study will depend on the empirical results rather than the theoretical presumptions. There may be a need for fiscal redistribution, especially with respect to targeted intergovernmental transfers [31], in favor of low-income clusters to narrow structural differences. Moreover, policies for promoting investment need to concentrate on enhancing the attractiveness of the region by developing infrastructure, human capital, and diversifying sectors [32]. Most importantly, the arguments related to sustainability results of the research conducted in this paper pertain only to the economic component of development, as evaluated via the trends in GRDP per capita and interprovincial disparity reduction [33]. Although the results obtained are important for the purposes of development policies, these cannot be regarded as a holistic analysis of the sustainability indicators from the perspective of environment or society. In general, the combination of results related to clustering and forecasting creates an empirical basis for the formulation of economic policies in Indonesia [34].

4. CONCLUSION

Based on the analysis of GRDP per capita across all Indonesian provinces using clustering, trendline modeling, and forecasting techniques in Tableau, the results indicate a clear economic disparity among regions. Cluster 1 represents the majority of provinces, characterized by low to medium GRDP per capita levels. Cluster 2 comprises resource-based provinces such as North Kalimantan and Riau Islands, which display GRDP per capita values above the national average. In contrast, cluster 3, which consists solely of DKI Jakarta and East Kalimantan, exhibits exceptionally high economic dominance compared to other regions. Trendline and forecasting projections further reveal that DKI Jakarta is expected to maintain stable growth in GRDP per capita through 2030, while East Kalimantan shows signs of stagnation. North Kalimantan demonstrates a positive growth trajectory, whereas West Papua experiences significant economic contraction. Similarly, East Nusa Tenggara shows steady economic growth, while Papua exhibits sharp fluctuations with an overall downward trend. These findings underscore the persistent unevenness of economic development in Indonesia. Provinces with diversified economies and strong infrastructural support tend to achieve stable growth, whereas those dependent on extractive industries or facing socio-political constraints often experience stagnation or decline. Accordingly, strategic interventions are required to accelerate development in lagging provinces to ensure that national economic growth becomes more inclusive and sustainable.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The research related to human use has been compiled with all the relevant national regulations and institutional policies in accordance with the tenets of the Helsinki Declaration and has been approved by the authors' institutional review board or equivalent committee.

DATA AVAILABILITY

The data used in this study are publicly available through Kaggle at https://www.kaggle.com/datasets/jocelyndumlao/inclusive-economics-growth-determinants/data, reference [15]. This research focuses on inclusive economic growth and its determinants in Indonesia. It uses yearly data from 2015 until 2021 in 34 provinces of Indonesia. The data were gathered from several reports from BPS, with reference to https://www.bps.go.id/en/publication/2025/04/11/95c729ee8c6fb5e2cb86b00f/produk-domestik-regional-bruto-provinsi-provinsi-di-indonesia-menurut-lapangan-usaha-2020-2024.html, reference number [16]. The variables included in the dataset are provinces, cities/regencies, percentage of poor people, regional GRDP (in billion rupiah), life expectancy, average school time, and expenses per capita.

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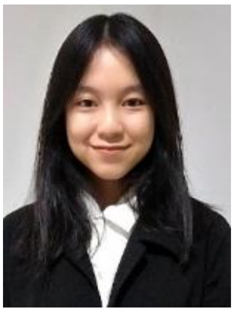

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