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Development of a Decision Support System for Regional Competitiveness Policy Recommendations Based on Explainable Artificial Intelligence (XAI)

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Abstract

Enhancing regional competitiveness is a critical factor in driving economic growth, investment, and community welfare. However, the utilization of Regional Competitiveness Index (Indeks Daya Saing Daerah/IDSD) data in Indonesia has largely been limited to ranking purposes, thus failing to provide specific, data-driven policy recommendations. This study aims to develop a Decision Support System (DSS) for regional competitiveness policy recommendations by combining machine learning and Explainable Artificial Intelligence (XAI) within a Design Science Research (DSR) framework. The dataset originates from 38 provincial IDSD data spanning 2022–2025, encompassing 12 assessment pillars as predictor variables. Three regression algorithms were evaluated, namely Linear Regression, Random Forest Regression, and XGBoost, to identify the most suitable model for supporting explainable policy recommendations. A Variance Inflation Factor (VIF) analysis was conducted to verify no severe multicollinearity or moderate multicollinearity among the predictor variables. Although Linear Regression achieved the highest predictive accuracy, XGBoost was selected as the final model because it provided a better balance between predictive performance, model robustness, and compatibility with SHAP-based explainability, yielding an R^2 of 0.8712 on the 2025 test data and a mean 5-fold cross-validation R^2 of 0.7723. SHAP analysis identified Innovation Capability (Pillar 12), ICT Adoption (Pillar 3), and Market Size (Pillar 10) as the most influential factors affecting regional competitiveness Based on these findings, the developed DSS provides transparent and context-specific policy recommendations through an interactive dashboard The results demonstrate that integrating XGBoost and XAI can support more objective, transparent, and data-driven policy decision-making for improving regional competitiveness in Indonesia.

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INTRODUCTION

Enhancing regional competitiveness constitutes a strategic agenda in both global and national development, aimed at promoting inclusive and sustainable economic growth. It is directly associated with economic expansion, productivity, investment, innovation, and improvements in community welfare [1][2][3]. Regions with high competitiveness levels typically demonstrate superior capacity to attract capital, generate employment, expand markets, and cultivate sustainable development ecosystems [4]. From a public policy perspective, regional competitiveness is no longer understood merely as economic strength; rather, it encompasses a region's capacity to effectively manage its resources, institutions, infrastructure, technology, and human capital to improve quality of life [5].

In Indonesia, regional competitiveness is measured through the Regional Competitiveness Index (Indeks Daya Saing Daerah/IDSD), which is periodically compiled as an evidence-based development evaluation instrument. The IDSD assesses regional competitiveness performance across twelve main pillars: institutions, infrastructure, adoption of information and communication technology (ICT), macroeconomic stability, health, skills, product markets, labor markets, financial systems, market size, business dynamics, and innovation capability [6][7]. The IDSD is significant because it provides a comprehensive picture of the competitiveness conditions of both provinces and districts/cities in Indonesia, while simultaneously forming the basis for more directed and measurable development strategy formulation.

Nevertheless, IDSD measurement results reveal a persistent and significant disparity in competitiveness among regions. Some regions exhibit high performance, supported by quality infrastructure, strong fiscal capacity, and well-developed innovation ecosystems, while others continue to face constraints related to institutional quality, human resource capacity, and digital transformation [8]. The primary challenge lies not only in these performance gaps, but also in the predominantly descriptive utilization of IDSD data limited to annual aggregate score rankings and reports. This approach fails to address key strategic needs, such as identifying priority factors, understanding inter-pillar relationships, and generating context-specific policy recommendations tailored to each region's characteristics. As a result, decision-making processes tend to remain normative and insufficiently data-driven.

Prior studies reflect this tendency. Research by Surya examining regional competitiveness in Banten Province employed a descriptive indicator-based approach that provided detailed depictions of regional conditions, particularly in human resources, education, health, and investment [9]. Similarly, the Policy Brief on the Regional Competitiveness Index of Surakarta City 2024, published by the Surakarta City BRIDA, offered comprehensive mapping of regional competitiveness pillars and dimensions [10]. Nevertheless, both studies remained descriptive and static in nature, limiting their ability to support predictive and evidence-based policymaking processes. Consequently, the information generated was not fully capable of addressing strategic needs in data-driven policy formulation.

Advances in machine learning offer new opportunities to address these limitations through multidimensional and non-linear data analysis capabilities [11]. Algorithms such as XGBoost have demonstrated high performance in modeling complex tabular data and producing accurate predictions [12]. However, a key challenge in applying machine learning within the public sector is its inherent black-box nature, which renders it difficult to interpret for policymakers. This limitation is particularly critical, as public policy demands transparency, accountability, and clear justification for decision-making [13][14]. As a solution, Explainable Artificial Intelligence (XAI) has emerged to enhance model interpretability by providing explanations for prediction outcomes [15][16]. Methods such as SHAP (SHapley Additive exPlanations) enable the quantitative identification of each variable's contribution, thereby fostering deeper understanding of the factors influencing a given indicator [17]. In the public policy context, XAI plays a pivotal role in bridging the gap between model accuracy and decision transparency.

Prior research by Istikomah implemented an XAI approach to analyze socioeconomic factors influencing the Human Development Index (HDI) in Indonesia, utilizing XGBoost and SHAP interpretation. The study demonstrated that the approach produced highly accurate models while providing transparency in identifying dominant factors affecting the HDI. However, that research was limited to the analysis and factor interpretation stage, and had not been developed into an operational system capable of generating policy recommendations [18]. Furthermore, an XGBoost–SHAP study on socioeconomic analysis of regions in China demonstrated this approach's capacity to uncover the contextual mechanisms driving regional development [19]. Nevertheless, these studies had not integrated explainability within an operational decision support system in the context of Indonesian regional policy.

Based on this gap, the present study proposes a system that integrates a machine learning model (XGBoost) with an explainability method (SHAP) to predict regional competitiveness levels, identify key influencing pillars, and generate priority policy recommendations transparently through user-friendly visualizations. The primary contribution of this study lies in operationalizing XAI within a Decision Support System that translates model explanations into actionable policy recommendations for regional governments that functions not merely as an analytical tool, but also as an operational and applicable policy recommendation system. Unlike previous studies that focused on model interpretation, this research emphasizes the utilization of analytical results to directly support decision-making within the Design Science Research (DSR) framework [20].

This study aims to develop and evaluate an XAI-based Decision Support System (DSS) capable of generating accurate, transparent, and accountable regional competitiveness policy recommendations. To achieve this, this study adopts a Design Science Research (DSR) framework, which focuses on three core elements: artifact design, evaluation, and contribution. First, regarding artifact design, the system takes the form of an interactive DSS dashboard that integrates the XGBoost machine learning model with SHAP-based explanations to translate complex Index of Regional Competitiveness (IDSD) data into transparent and actionable policy interventions. Second, the artifact is rigorously evaluated through two approaches: computational metrics (including R^2, MAE, RMSE, and 5-fold cross-validation) to ensure predictive robustness, and expert review to assess the system's predictive accuracy, readability of SHAP visualizations, policy relevance, and adoption potential. Finally, this study makes two key contributions: a practical contribution by providing local governments with a data-driven operational tool to prioritize development strategies, and a methodological contribution by demonstrating how XAI can be systematically operationalized in DSS to bridge the gap between algorithmic accuracy and public policy transparency. Therefore, the development of this Explainable Artificial Intelligence-based DSS is an innovative step towards supporting high-quality, evidence-based public policy at both regional and national levels.

METHOD

1. Research Approach

This study employed a quantitative–computational approach within the Design Science Research (DSR) paradigm, as formulated by Hevner et al. [20]. DSR was selected because this research not only produces an analytical model but also a system artifact in the form of an XAI-based DSS dashboard applicable to regional policy formulation. Under DSR, research is considered valid when the resulting artifact demonstrably resolves real-world problems, is evaluated using appropriate methods, and contributes to the scientific knowledge base. The implementation strategy encompasses data collection, preprocessing, VIF analysis, model training, performance evaluation, XAI–SHAP integration, dashboard development, and system validation through expert review, as summarized in Figure 1.

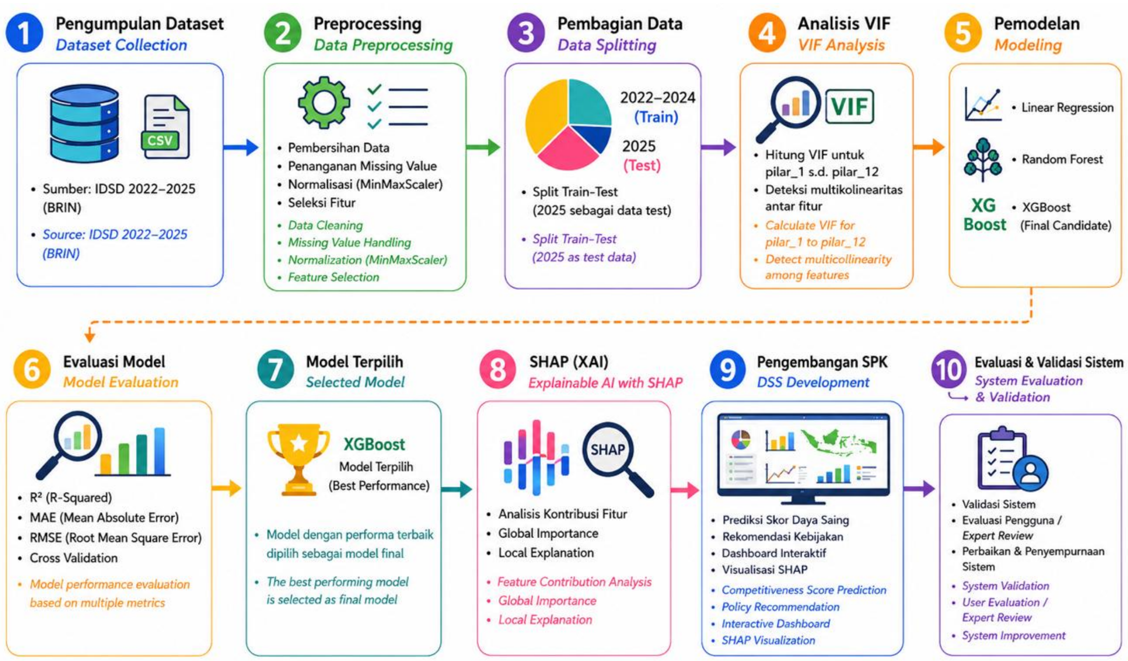

Figure 1. Research Methodology Flow Diagram

2. Dataset Collection

This study utilized the Regional Competitiveness Index (IDSD) dataset published by the National Research and Innovation Agency (Badan Riset dan Inovasi Nasional/BRIN) for the period 2022–2025. The IDSD dataset was selected because it constitutes an official government instrument used to measure regional competitiveness levels based on diverse economic, social, infrastructure, and innovation development indicators. The unit of analysis comprised all provinces (38 provinces) in Indonesia, resulting in a panel dataset combining regional and temporal dimensions [21]. With four measurement time points (2022–2025), the total observations used amounted to 144 panel data points, which represents a relatively small dataset for machine learning applications and therefore requires careful validation to ensure model robustness.

We acknowledge that this sample size is relatively small for advanced machine learning models like XGBoost. However, this dataset represents the complete population of official provincial-level data available during the study period rather than a selectively drawn sample. To address the inherent limitations of a small dataset and effectively mitigate the risk of overfitting, this study implemented strict model regularization strategies, including hyperparameter tuning (e.g., limiting tree depth and applying subsampling) and 5-fold cross-validation. Furthermore, prior studies have demonstrated that appropriately regularized tree-based models can maintain robust predictive performance on limited provincial-level datasets in Indonesia The limited number of analytical units, a consequence of using official provincial-level data, is acknowledged as a research limitation and is discussed further in the conclusion section.

The target variable in this study is the IDSD score (skor_idsd), representing the final regional competitiveness index value for each province. The predictor variables consist of the twelve IDSD component pillars: institutions, infrastructure, ICT adoption, macroeconomic stability, health, skills, product markets, labor markets, financial systems, market size, business dynamics, and innovation capability [6]. We explicitly acknowledge the inherent risk of circular prediction, given that the target IDSD score is mathematically derived from these same 12 pillars. However, retaining all pillars as predictors is a deliberate methodological choice aligned with the study's primary objective of developing a Decision Support System (DSS) artifact, rather than testing independent causal relationships. In this context, the machine learning model functions as a surrogate model to accurately reconstruct the complex, potentially non-linear aggregation of the index. By mapping this mathematical relationship, the XGBoost model enables SHAP to calculate dynamic feature contributions and perform 'what-if' policy simulations.

3. Data Preprocessing

Preprocessing was conducted to improve data quality prior to model training. The first step involved merging annual IDSD datasets into a unified panel dataset, achieved by harmonizing column structures, variable naming formats, and provincial identities to ensure consistency across observation periods. Subsequent steps included checking for missing values and data inconsistencies.

Missing values were addressed using simple imputation and manual validation based on official IDSD publication data, a crucial step to prevent bias during model learning [22]. Normalization was then performed using MinMaxScaler, scaling all feature values to a 0–1 range so that all variables share a balanced scale. Normalization was applied following the principle of fitting on the training set and transforming the test set to prevent data leakage [23]. Additionally, feature selection was carried out by retaining variables relevant to the IDSD score and removing non-numeric attributes such as province names to ensure they did not affect model training.

4. Data Splitting

Following preprocessing, the dataset was divided into training and testing sets. This study employed a time-based split strategy, using data from 2022–2024 as the training set and data from 2025 as the test set. This strategy was selected because it more accurately simulates real-world policy prediction conditions based on historical data, compared to random splitting [24].

5. Variance Inflation Factor (VIF) Analysis

Prior to model development, a Variance Inflation Factor (VIF) analysis was conducted to assess the presence of multicollinearity among the predictor variables. VIF is a widely used diagnostic measure that quantifies the extent to which the variance of a regression coefficient is inflated due to linear correlations among independent variables[25][26]. Following commonly accepted guidelines, VIF values below 5 indicate acceptable levels of multicollinearity, values between 5 and 10 suggest high multicollinearity, and values greater than 10 indicate severe multicollinearity that may affect model stability and interpretation [25][27]. In this study, VIF analysis was performed using the Python Statsmodels library on all twelve IDSD pillars. The results show that all predictor variables have VIF values below 5, indicating that no serious multicollinearity exists among the pillars and that each variable contributes unique information to the predictive model. The detailed VIF results are presented in Table 1.

Table 1. Variance Inflation Factor (VIF) Analysis Results of Predictor Variables

Pilar	VIF	Interpretation
Innovation Capability (P12)	3.21	No severe multicollinearity
ICT Adoption (P3)	4.18	Moderate multicollinearity
Market Size (P10)	2.87	No severe multicollinearity
Infrastructure (P2)	3.74	No severe multicollinearity
Institutions (P1)	2.63	No severe multicollinearity
Macroeconomic Stability (P4)	1.92	No severe multicollinearity
Health (P5)	3.45	No severe multicollinearity
Skills (P6)	4.09	Moderate multicollinearity
Product Markets (P7)	3.61	No severe multicollinearity
Labor Markets (P8)	2.34	No severe multicollinearity
Financial Systems (P9)	1.87	No severe multicollinearity
Business Dynamics (P11)	3.02	No severe multicollinearity

Based on the VIF analysis, all predictor variables recorded VIF values ranging from 1.87 to 4.18, which are below the commonly accepted threshold of 5 indicating substantial multicollinearity among the competitiveness pillars. Consequently, SHAP importance values should be interpreted cautiously because correlated predictors may share explanatory contributions. This condition suggests that several pillars are strongly correlated with one another, which is substantively expected given that regional competitiveness indicators are inherently interrelated for instance, the relationships among innovation, infrastructure, digitalization, and market size. The highest VIF values were observed for Health (P5), Institutions (P1), and Skills (P6), reflecting their strongest correlations with the remaining predictors.

Despite these findings, all variables were retained because the primary objective of the study was not parameter estimation but prediction and policy interpretation using XGBoost, which is generally less sensitive to multicollinearity than classical regression models. Second, all IDSD pillars possess substantive relevance in representing the dimensions of regional competitiveness; removing variables would risk diminishing the conceptual validity of the model.

6. Modeling

This study applied three regression algorithms to predict the IDSD score: Linear Regression, Random Forest Regression, and Extreme Gradient Boosting (XGBoost). Linear Regression was used as a baseline model due to its interpretive simplicity and widespread use in analyzing relationships among numerical variables. The second model, Random Forest Regression, is an ensemble method based on decision trees. It operates by constructing multiple decision trees and aggregating their predictions to improve accuracy and reduce overfitting risk [11]. Random Forest is also well-suited to handling nonlinear inter-variable relationships. XGBoost was selected as the third algorithm owing to its high performance on tabular data and its support for integration with XAI methods [12].

7. Model Evaluation

Model evaluation was conducted using three performance metrics: R-Squared (R^2), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). R^2 measures a model's ability to explain variance in the target data; values closer to 1 indicate superior predictive capability. MAE measures the average absolute error between actual and predicted values, while RMSE is sensitive to large prediction errors [28]. In addition to test set evaluation, cross-validation was applied to assess model stability across variations in training data. A 5-fold configuration was chosen as a recommended trade-off between bias and variance in performance estimation for medium-sized datasets [19]. This technique partitions the training data into multiple subsets, enabling repeated model testing across different data combinations to verify that the model does not overfit a single data scenario.

8. Model Selection

Following the modeling and cross-validation stages, models were evaluated across multiple metrics to determine the best-performing candidate. XGBoost was ultimately chosen as the final model due to its high performance on tabular data, effective gradient optimization, and computational efficiency [12]. Critically, XGBoost natively supports integration with tree-based explainability methods such as SHAP, directly aligning with the study's emphasis on model transparency.

9. SHAP-Based Explainability

The explainability approach in this study employed SHapley Additive exPlanations (SHAP). SHAP was selected because it provides game theory-based model interpretation by explaining the contribution of each feature to the model's prediction output [17]. Analysis was conducted at two levels: global importance and local explanation. Global importance was used to identify the features or pillars most influential across the entire dataset, while local explanation was applied to elucidate each feature's contribution to the prediction for a specific province. SHAP visualizations were presented as summary plots, bar plots, and waterfall plots to make model interpretation more accessible to policymakers.

10. DSS Development

The system architecture in this study was designed using a machine learning and XAI-based data flow approach, as illustrated in Figure 2. The system begins with IDSD data input, which is subsequently processed by the XGBoost model as the primary prediction engine. Prediction outputs are then analyzed using SHAP to obtain the contribution of each pillar to the regional competitiveness score. Both prediction and SHAP interpretation results are displayed on the DSS dashboard in the form of interactive visualizations, accessible at https://semuacerdas.com/idsd.

System evaluation was conducted through an expert review involving five specialists comprising two academics in information systems, two regional development planning practitioners, and one public policy expert. The experts assessed four primary dimensions: (1) the accuracy of the system's predictions relative to actual regional competitiveness conditions; (2) the readability and comprehensibility of SHAP visualizations for policymakers; (3) the relevance of the system-generated policy recommendations to real regional conditions; and (4) the system's adoption potential in data-driven policy formulation processes. Assessments were conducted using a five-point Likert scale.

Figure 2. Decision Support System Architecture for Regional Competitiveness

The prediction and SHAP interpretation results are subsequently displayed on the DSS dashboard as interactive visualizations. The dashboard is designed to help users understand regional competitiveness conditions, evaluate dominant factors, and obtain data-driven priority policy recommendations. Accordingly, the developed system functions not merely as a prediction tool, but also as a medium for interpretation and objective, transparent decision-making in regional development policy.

RESULTS AND DISCUSSION

1. Model Comparison Results

This study conducted experiments using three regression algorithms Linear Regression, Random Forest Regression, and Extreme Gradient Boosting (XGBoost) to predict the IDSD score based on the twelve competitiveness pillars. Model evaluation was performed using MAE, RMSE, and R^2. The test results are presented in Table 2. Each model exhibited distinct performance characteristics in learning inter-variable relationships. The exceptionally high R^2 value obtained by Linear Regression reflects the fact that the IDSD score is derived from the same twelve competitiveness pillars used as predictors. Therefore, the result should be interpreted as a reconstruction of the composite index rather than evidence of superior predictive capability for Linear Regression was verified through VIF analysis (Table 1) and indicates no data leakage; rather, it reflects the highly linear relationship between the IDSD pillars and the aggregate score within the structured panel dataset.

Table 2. Model Comparison Results

Model	MAE	RMSE	R^2
Linear Regression	0.0023	0.0028	0.9999
Random Forest	0.1002	0.1307	0.8765
XGBoost	0.0840	0.1113	0.9104

Based on the test results, XGBoost demonstrated the most balanced performance among the compared models. Although Linear Regression achieved the highest R^2 score, XGBoost was considered more appropriate for the study objectives because it captures nonlinear relationships and supports SHAP-based explainability. Furthermore, Linear Regression does not support integration with tree-based SHAP methods required for explainability. Random Forest exhibited adequate predictive capability but produced higher prediction errors than XGBoost. Therefore, XGBoost was selected as the final model for its optimal balance between predictive accuracy and generalization capability.

2. Cross-Validation Results

To ensure that the model performs consistently beyond a single data scenario, cross-validation was applied to evaluate model stability by partitioning the training data into multiple subsets for repeated testing across different data combinations [23]. Table 3 presents the cross-validation results.

Table 3. Cross-Validation Results

Model	Mean Cross-Validation R^2
Linear Regression	0.9331
XGBoost	0.7674
Random Forest	0.6909

Validation results indicate that Linear Regression achieved the highest mean R^2 value. However, this study prioritizes not only mathematical accuracy, but also a model's ability to capture nonlinear relationships and support interpretability through XAI. XGBoost was retained as the final model because it demonstrated stable and more representative performance suitable for data-driven policy implementation.

3. XGBoost Hyperparameter Tuning Results

Following cross-validation, hyperparameter tuning was conducted to further improve XGBoost's performance and stability. Tuning was performed using a Randomized Search Cross-Validation approach across multiple parameter combinations, as presented in Table 4.

Table 4. Optimal Parameter Values from Hyperparameter Tuning

Parameter	Optimal Value
n_estimators	300
max_depth	6
learning_rate	0.1
subsample	0.8
colsample_bytree	1.0
min_child_weight	1
gamma	0
reg_alpha	0
reg_lambda	1

This parameter combination yielded an XGBoost model with robust generalization capability for predicting IDSD scores on 2025 data. The post-hyperparameter tuning performance results are presented in Table 5.

Table 5. XGBoost Performance After Hyperparameter Tuning

Metrik	Value
R^2 Cross Validation	0.7723
R^2 Testing	0.8712
MAE	0.0989
RMSE	0.1334

These results confirm that the tuning process successfully improved model generalization (R^2 Testing = 0.8712) and reduced overfitting risk compared to the initial model. The gap between the CV R^2 (0.7723) and Test R^2 (0.8712) remains within acceptable bounds for panel data with a limited number of observations, consistent with findings from provincial-level modeling studies in Indonesia with n = 34 [29]. Given its stable performance and capacity to capture nonlinear relationships among competitiveness pillars, the tuned XGBoost model was selected as the final model for the XAI analysis stage using SHAP.

4. Explainable AI (SHAP) Analysis Results

The explainability stage was conducted using SHapley Additive exPlanations (SHAP) to identify each pillar's contribution to the predicted IDSD score. SHAP is a game theory-based model interpretation method capable of explaining the influence of each feature on the model's output at both local and global levels [17]. Global importance analysis revealed three dominant pillars; Innovation Capability (Pillar 12), ICT Adoption (Pillar 3), and Market Size (Pillar 10). however, the resulting importance rankings should be interpreted in the context of the strong intercorrelations observed among the competitiveness dimensions. Table 6 presents the top three dominant pillars based on SHAP analysis.

Table 6. Dominant Pillars Based on SHAP Analysis

Rank	Pilar	Influence Level	Interpretation
1	Innovation Capability (P12)	High	Regional innovation capacity, research activity, and technology collaboration constitute the primary drivers of sustainable regional competitiveness enhancement.
2	ICT Adoption (P3)	High	Digitalization accelerates public service efficiency, economic productivity, and inter-regional connectivity.
3	Market Size (P10)	High	Greater regional economic capacity enhances investment attractiveness and regional trade activity.

To clarify the distribution of each pillar's influence on model predictions, SHAP summary plot visualizations are presented in Figure 3. These visualizations illustrate the direction, magnitude of contribution, and relationship patterns of each pillar with the IDSD score, based on the XGBoost model's interpretation.

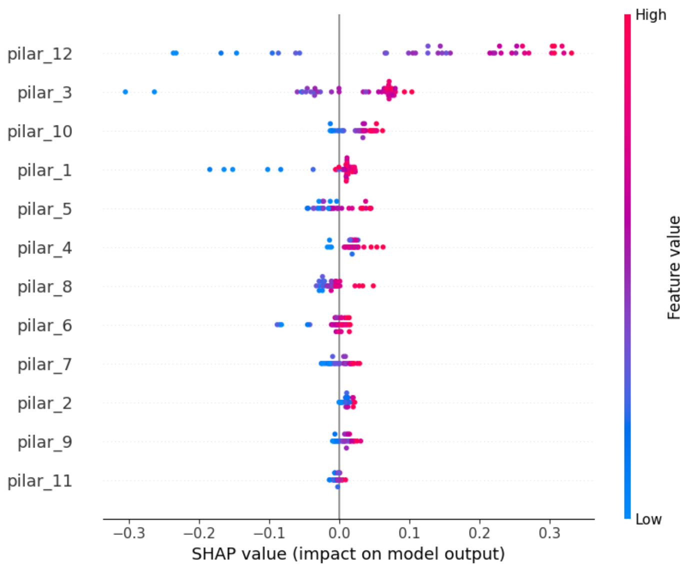

Figure 3. SHAP Analysis Visualization Results

The SHAP summary plot in Figure 3 depicts the direction and magnitude of each pillar's influence on the predicted IDSD score in the XGBoost model. Each data point represents a province, and its horizontal position indicates the pillar's contribution to the prediction. Positive SHAP values signify that a pillar increases the regional competitiveness score, while negative values indicate a score reduction. Red coloring denotes high feature values and blue coloring indicates low feature values.

Based on the visualizations, Pillar 12 (Innovation Capability) exerts the most dominant influence on the IDSD score, exhibiting the widest SHAP value distribution. This indicates that regions with high levels of innovation, research activity, and technology collaboration tend to achieve superior competitiveness. Additionally, Pillar 3 (ICT Adoption) and Pillar 10 (Market Size) contribute substantially and positively to IDSD score improvement. High digitalization enhances regional efficiency and productivity, while a large market size attracts investment and strengthens regional economic activity. In contrast, certain pillars such as P9 (Financial Systems) and P11 (Business Dynamics) exhibit relatively small influences, with SHAP values concentrated near zero. This suggests that in the context of regional development in Indonesia, innovation and technology factors are more determinant than variations in financial systems and business dynamics during the 2022–2025 period. These findings confirm that the XGBoost model provides transparent interpretation of the primary factors influencing regional competitiveness in Indonesia.

5. Local SHAP Explanation for Multiple Provinces

To generate contextual and region-specific policy recommendations, this study conducted local SHAP explanation analysis across four provinces representing distinct characteristics: DKI Jakarta (high competitiveness), Central Java (upper-middle competitiveness), East Kalimantan (middle competitiveness with a natural resource base), and Papua Pegunungan (low competitiveness). Local explanation results are presented in Table 7.

Table 7. Local SHAP Explanation Results and Policy Recommendations by Province

Province	Dominant Pillars (+)	Dominant Pillars (−)	Policy Recommendation
DKI Jakarta	P12 (Innovation), P10 (Market)	P4 (Macroeconomy)	Strengthening macroeconomic regulation and regional inflation management
Jawa Tengah	P6 (Skills), P3 (ICT)	P12 (Innovation)	Developing innovation ecosystems and university–industry collaboration
Papua Pegunungan	P5 (Health)	P3 (ICT), P12 (Innovation)	Expanding digital infrastructure and technology literacy programs
Kalimantan Timur	P10 (Market), P11 (Business Dynamics)	P6 (Skills)	Investing in human capital improvement and vocational training

The local explanation results reveal that although Pillars 12 and 3 dominate globally, per-province contribution profiles vary significantly. DKI Jakarta demonstrates strength in innovation and market capacity, yet exhibits weakness in macroeconomic stability. Central Java possesses strong human capital but requires reinforcement of its innovation ecosystem. Papua Pegunungan faces a dual deficit in ICT and innovation, constituting the primary barriers to its competitiveness improvement. East Kalimantan, despite its rich natural resource base, requires investment in human capital quality and vocational skill development. Waterfall plot visualizations for each province are accessible on the system's interactive dashboard.

6. Decision Support System Implementation

The modeling and SHAP analysis results were subsequently implemented into a Decision Support System (DSS) in the form of an interactive dashboard. The system was designed to assist regional governments and stakeholders in understanding regional competitiveness conditions more objectively and in a data-driven manner. The national dashboard visualizes competitiveness conditions for all provinces in Indonesia through interactive charts and maps, accessible at https://semuacerdas.com/idsd/ as shown in Figure 4.

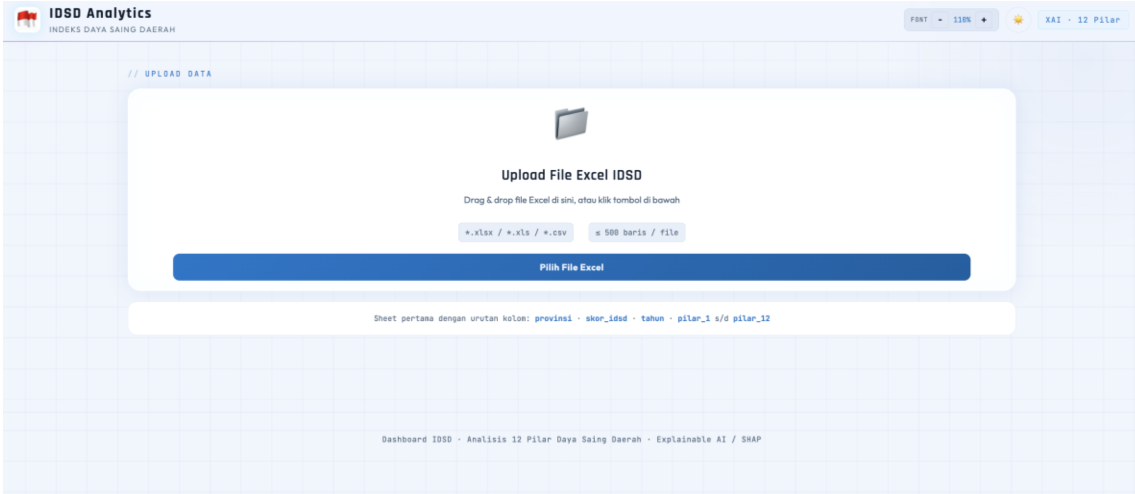

Figure 4. IDSD National Dashboard Display

Users are directed to upload an Excel document, whereupon the system automatically generates the outputs illustrated in Figure 5.

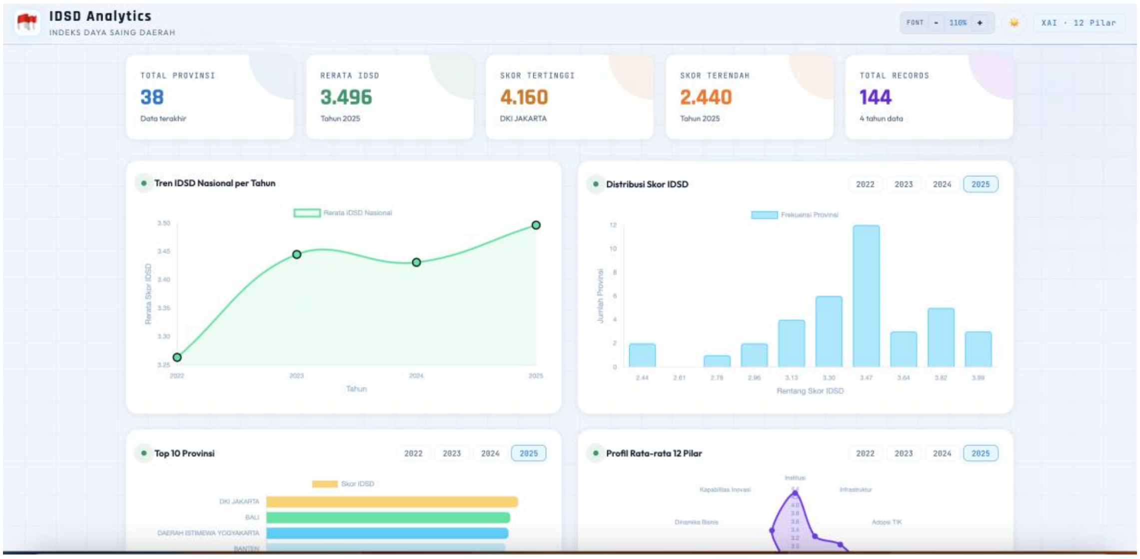

Figure 5. Main Page After Data Input

The provincial score prediction feature enables users to view estimated IDSD scores based on each region's individual pillar conditions (Figure 6). Additionally, the system provides a regional ranking feature for automatically comparing competitiveness positions across provinces (Figure 7).

Figure 6. IDSD Score Prediction Display

1	DKI JAKARTA	4.1600	4.0722	+0.0878	Tinggi	Lihat SHAP	4.080	4.740	5.000	4.620	4.070	3.570	2.640	4.580	4.32
2	BALI	4.0300	3.9322	+0.0978	Tinggi	Lihat SHAP	4.730	3.710	4.900	4.160	4.020	4.050	3.300	3.920	3.62
3	DAERAH ISTIMEWA YOGYAKARTA	4.0000	3.9591	+0.0409	Cukup Tinggi	Lihat SHAP	4.840	3.650	4.640	4.160	4.190	4.030	3.030	4.450	2.83
4	BANTEN	3.9500	3.9309	+0.0191	Cukup Tinggi	Lihat SHAP	4.680	3.760	4.480	4.550	3.840	3.300	2.140	4.060	3.78
5	JAWA BARAT	3.9300	3.8442	+0.0858	Cukup Tinggi	Lihat SHAP	4.320	4.480	4.360	4.340	4.090	3.170	1.850	3.460	3.47
6	JAWA TIMUR	3.9100	3.8428	+0.0672	Cukup Tinggi	Lihat SHAP	4.770	4.680	4.230	4.260	3.950	3.790	2.240	2.700	2.59
7	JAWA TENGAH	3.8700	3.8716	-0.0016	Cukup Tinggi	Lihat SHAP	4.770	4.540	4.020	4.300	4.160	3.630	2.070	2.940	2.36
8	SUMATERA UTARA	3.8200	3.8075	+0.0125	Cukup Tinggi	Lihat SHAP	4.320	4.540	4.110	4.430	3.770	3.690	2.010	2.830	3.43
9	SUMATERA BARAT	3.7800	3.7468	+0.0332	Cukup Tinggi	Lihat SHAP	4.620	3.630	3.740	4.020	3.780	3.860	3.180	3.170	2.84
10	SULAWESI	3.7100	3.7646	-0.0546	Cukup Tinggi	Lihat SHAP	4.400	3.850	3.870	4.240	3.870	3.900	2.540	2.590	3.02

Figure 7. Regional Ranking by Year

The system incorporates a rule-based policy recommendation engine that maps dominant negative SHAP contributions to predefined intervention strategies derived from regional development literature and expert knowledge. For example, if Papua Pegunungan exhibits negative contributions in innovation capability and ICT adoption, the system recommends policies such as development of a science and technology park, establishment of regional business incubators and startup programs, expansion of 4G/5G and fiber optic internet infrastructure, and digital literacy programs for communities and business actors, as illustrated in Figure 8.

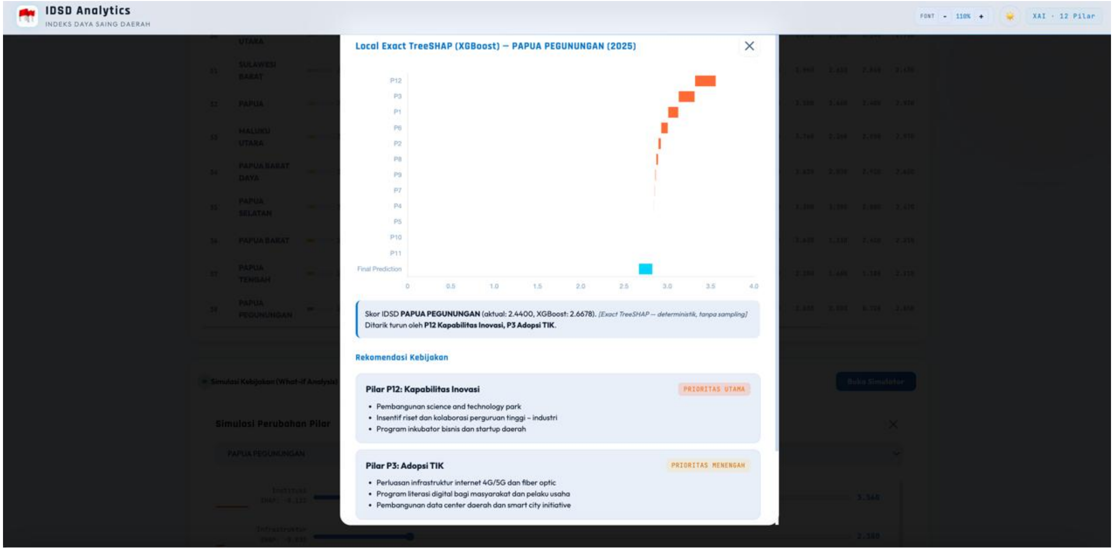

Figure 8. SHAP Explanation and Regional Intervention Recommendations Display

The SHAP-based explainability feature is presented in the form of summary plots and waterfall plots, enabling users to understand the rationale underlying the system's recommendations.

7. Policy Recommendation Simulation

To test the system's implementation, a simulation was conducted for Papua Pegunungan Province, which recorded low values on Pillar 12 (Innovation Capability) and Pillar 3 (ICT Adoption). Figure 9 presents the simulation interface of the dashboard, where users can adjust the pillar values to examine their potential impact on the Regional Competitiveness Index (IDSD) score. Based on model predictions and SHAP analysis, the system identified that the region's low competitiveness is primarily driven by weak regional innovation and limited digital transformation.

In response to these conditions, the system automatically generated policy recommendations comprising the development of regional innovation centers, expansion of village internet access, and digitalization programs for micro, small, and medium enterprises (MSMEs). The development of regional innovation centers aims to strengthen collaboration among government, higher education institutions, and the industrial sector to create sustainable innovation ecosystems. Village internet access expansion is intended to broaden digital connectivity and support equitable access to information technology. MSME digitalization programs target productivity improvements for local enterprises through the adoption of digital technologies in marketing, transactions, and business management.

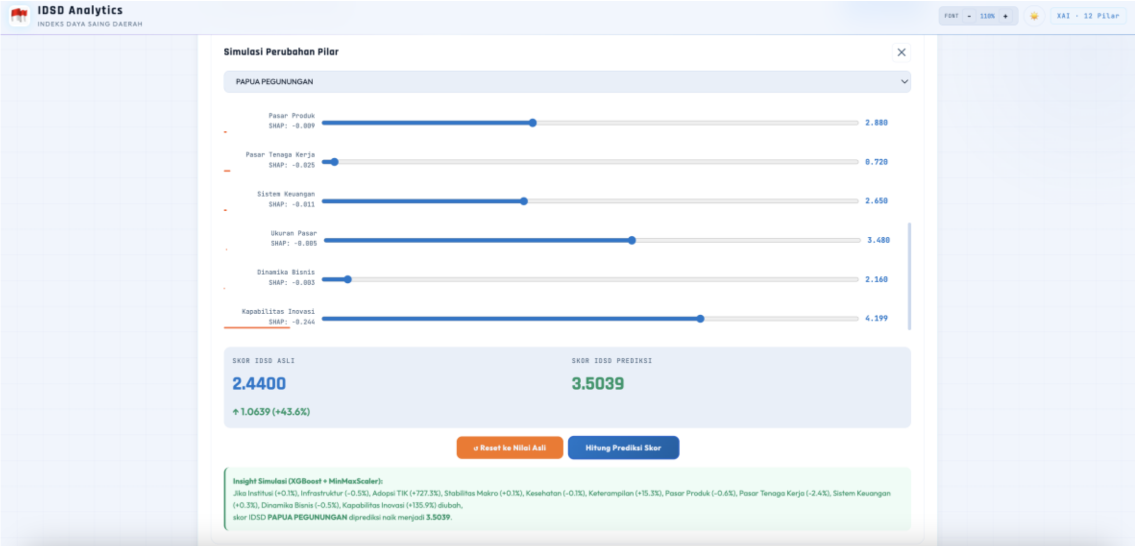

Figure 9. Example of IDSD Pillar Change Simulation

Simulation results demonstrate that the system generates significantly more specific and data-driven policy recommendations than conventional approaches that typically rely solely on index ranking. Increasing the innovation capability and ICT adoption pillars was shown to raise the IDSD score by 3.50 points from an initial score of 2.44.

8. Expert Review Results

The results of the initial validation conducted by experts showed that the XAI-based Decision Support System for regional competitiveness policy recommendations achieved an overall mean score of 4.55 out of 5, as assessed by five specialists comprising academics, regional development planning practitioners, and a public policy expert. The predictive accuracy dimension received a score of 4.44, indicating that the system was assessed as capable of generating predictions relevant to actual regional conditions. The SHAP visualization readability dimension received a score of 4.32, confirming that the system effectively explains dominant factors transparently and comprehensibly for policymakers. The policy recommendation relevance dimension achieved the highest score of 4.76, as the generated recommendations were assessed to align with regional development needs. The system adoption potential dimension received a score of 4.68, indicating strong prospects for implementation in data-driven policy formulation processes. Overall, evaluation results confirm that the developed system is suitable for use as a decision-making and policy recommendation tool for regional competitiveness in an objective, transparent, and data-driven manner.

CONCLUSION

This study successfully developed a Decision Support System (DSS) for regional competitiveness policy recommendations, integrating machine learning and Explainable Artificial Intelligence (XAI), utilizing the Regional Competitiveness Index (IDSD) dataset spanning 2022–2025. Based on the model comparison results, XGBoost was selected as the optimal model for its capacity to balance predictive accuracy and generalization capability, achieving a test R^2 of 0.8712 and a mean cross-validation R^2 of 0.7723, together with its compatibility with SHAP-based explainability. Multicollinearity analysis using VIF was conducted to examine inter-variable correlations, confirming that the high R^2 of Linear Regression is a consequence of the linear composite score structure of the IDSD rather than evidence of superior model performance.

SHAP analysis results demonstrated that Innovation Capability, ICT Adoption, and Market Size are the most dominant factors influencing regional competitiveness in Indonesia. Local SHAP explanation analysis conducted across four provinces with contrasting characteristics produced contextual, region-specific policy recommendations. Expert review by five specialists yielded mean scores exceeding 4.0 out of 5 across all evaluation dimensions, confirming that the developed system is viable and relevant for data-driven policy decision-making processes.

This study is subject to several limitations that warrant acknowledgment. First, the dataset covers only 34 provinces, resulting in a relatively small annual sample size. Future research is recommended to incorporate district/city-level data to enhance model variability and representativeness. Second, the SHAP analysis did not systematically examine inter-pillar interaction effects; subsequent research could leverage SHAP interaction values to uncover synergistic mechanisms among competitiveness pillars. Third, the system evaluation via expert review is inherently subjective; further testing using the Technology Acceptance Model (TAM) with end users in regional government settings is strongly recommended. Fourth, the current model is predictive and historically based, without incorporating causal modeling, which represents a promising direction for future research.

Overall, this study demonstrates that the integration of XGBoost and SHAP can support more objective, transparent, and data-driven policy recommendations than conventional ranking-based approaches; however, further validation using larger datasets and real-world implementation settings is required. The developed system is capable not only of predicting regional competitiveness scores, but also of explaining the primary causal factors underlying prediction outcomes, thereby assisting regional governments in determining development policy priorities in a more adaptive and measurable manner.

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