Analysis of Heterogeneity in Digital Economy Policy Effects Using XGBoost-Causal Tree

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ABSTRACT Addressing the limitations of traditional policy impact evaluation methods in accurately capturing the heterogeneous characteristics of digital economy policies while accounting for sample selection bias and complex causal relationships, this paper constructs an XGBoost-Causal Tree integrated analytical framework to systematically investigate policy effect differentiation characteristics. As digital economy development increasingly relies on advanced communication infrastructure and electromagnetic information transmission technologies, accurately evaluating policy heterogeneity has become essential for supporting intelligent industrial transformation and digital connectivity. First, drawing upon policy evaluation theory, machine learning, and causal inference theory, the core dimensions and evaluation metrics for policy effect differentiation are established. Second, based on panel data from 30 Chinese provinces spanning 2011–2022, a multidimensional dataset (DEP-2024) incorporating economic foundations, industrial structure, digital infrastructure, and related factors is constructed. Third, a three-step analytical framework consisting of Propensity Score Matching, XGBoost feature selection, and Causal Tree heterogeneity decomposition is designed to identify key influencing factors and quantify differentiated policy effects across heterogeneous groups. Finally, policy heterogeneity is validated from the perspectives of regional development, industrial structure, and digital infrastructure, and targeted optimization strategies are proposed. The proposed framework provides a reliable data-driven approach for policy assessment and offers valuable insights for digital infrastructure planning and intelligent resource allocation in future electromagnetic information and communication environments.

INDEX TERMS digital economy policy, XGBoost, causal tree, policy heterogeneity, electromagnetic information infrastructure

I. INTRODUCTION

A. RESEARCH BACKGROUND

THE digital economy, serving as the core engine driving high-quality economic development, has emerged as a new engine for global economic growth, fundamentally transforming traditional sectors like the industry through data-driven design, smart manufacturing, and e-commerce platforms [1]. China places high importance on the development of the digital economy, successively issuing policy documents such as the "Overall Plan for Building a Digital China" and the "14th Five-Year Plan for Digital Economy Development" to promote the deep integration of digital technologies with the real economy [2]. By 2023, China's digital economy reached 55.6 trillion yuan, accounting for 41.5% of GDP, demonstrating the remarkable effectiveness of digital economy policies [3-5].

Current Research Status at Home and Abroad：

1.Research on Evaluating the Effects of Digital Economy Policies

Overseas research in the field of digital economy policy evaluation began earlier, forming diversified evaluation systems [6-8]. A Stanford University team employed a difference-in-differences approach to assess the impact of digital infrastructure policies on regional economic growth, revealing significant regional variations in policy effects [9]. The European Commission utilized synthetic control methods to analyze the employment-boosting effects of digital skills training policies, confirming group heterogeneity in policy outcomes [10]. Theoretically, international scholars have focused on policy impact mechanisms, proposing the "digital infrastructure - tech nological innovation - economic growth" transmission pathway [11]. Empirical studies by some researchers indicate that industrial structure and human capital levels are key determinants of digital economy policy effectiveness [12]. However, most foreign studies are based on developed country contexts, exhibiting limited applicability to the policy environments and economic characteristics of developing nations [13-16].

2.Research on Methods for Analyzing Policy Effect Heterogeneity

Traditional heterogeneity analysis primarily relies on linear methods such as panel regression and interaction term models. Internationally, Angrist et al. proposed the Local Average Treatment Effect (LATE) framework, providing a theoretical foundation for assessing heterogeneous effects [17]. Imbens et al. employed propen sity score matching to evaluate policy effects across heterogeneous groups through stratified matching [18]. Domestically, scholars predominantly employ propensity score regression to analyze policy effect heterogene ity across dimensions such as region, industry, and enterprise scale [19]. Some researchers utilize threshold regression models to identify critical thresholds and interval differences in policy effects [20].

With the advancement of machine learning, heterogeneity analysis methods are increasingly shifting toward nonlinear, data-driven approaches. International researchers have applied algorithms like random forests and gradient-boosted trees to policy effect evaluation, enhancing the precision of identifying heterogeneous characteristics [21]. Athey et al. proposed the Causal Tree algorithm, which achieves precise estimation of treatment effects through recursive sample partitioning [22]. Domestic scholars have also begun exploring machine learning applications in policy evaluation: Zhang Min et al. employed XGBoost models to screen key factors influencing policy effects, providing variable support for heterogeneity analysis [23]; Liu Jing et al. combined Causal Trees with synthetic control methods to study regional policy effect heterogeneity [24].

However, existing research still has shortcomings: the integration of machine learning algorithms with causal inference theory remains superficial, often leading to "causal ambiguity"; there is a lack of a mature integrated framework encompassing "feature selection - heterogeneity decomposition - effect quantification"; and the adaptability to heterogeneity analysis for complex policies like digital economy policies is insufficient.

B. RESEARCH CONTENT AND TECHNICAL APPROACH

1) RESEARCH CONTENT

Theoretical framework for digital economy policy effect heterogeneity: Clarify the core essence and transmis sion mechanisms of digital economy policies, defining key dimensions of policy effect heterogeneity (region, industry, development stage).

Empirical analysis and policy recommendations: Conduct heterogeneity analy sis using an integrated framework to identify critical influencing factors and heterogeneous groups, proposing targeted policy optimization suggestions.

2) TECHNICAL APPROACH

The research follows a logical sequence of "theoretical construction - data preparation - framework design - empirical analysis - policy optimization":

- Theoretical Layer: Systematize theories related to policy evaluation, causal inference, and machine learning to clarify core dimensions of policy effect heterogeneity.
- Data Layer: Collect multidimensional panel data, perform preprocessing, variable screening, and dataset construction.

  Framework layer: Designed a three-step analytical process—"propensity score matching to eliminate selection bias → XGBoost to screen key influencing factors → Causal Tree to decompose heterogeneous effects";

  Empirical layer: Conducted empirical research based on the constructed framework, multidimensionally validating the characteristics of policy effect heterogeneity;

  Policy layer: Based on empirical findings, proposed differentiated optimization recommendations for digital economy policies, forming a closed-loop research cycle that can guide targeted government support and investment in the digitalization and intelligent transformation of the industry.

II. THEORETICAL FOUNDATIONS

A. CORE THEORIES OF DIGITAL ECONOMY POLICY

Definition and Classification of Digital Economy Policy

Digital economy policy refers to institutional arrangements and measures formulated by governments to promote digital economic development and regulate its order. Based on policy objectives, it can be categorized as:

Supply-side policies: Focusing on supply-side elements such as digital infrastructure construction, digital technology R&D, and digital talent cultivation, e.g., the "Broadband China" strategy and support policies for digital economy industrial parks;

Demand-side policies: Stimulate digital economic growth by expanding demand for digital products and services, such as digital consumption subsidies and e-commerce support policies;

Regulatory policies: Standardize the digital economic market order, ensure data security and fair competition, such as the Data Security Law and anti-monopoly policies for platform economies.

Transmission Mechanisms of Digital Economy Policies
Digital economy policies influence economic development through dual pathways of "direct effects + indirect effects":

Direct Effects: Directly promote digital economy development by improving digital infrastructure and reducing digital technology application costs;

Indirect Effects: Indirectly drive traditional industry transformation and regional economic growth through channels such as technology spillovers, industrial convergence, and efficiency gains.

B. THEORY OF POLICY EFFECT HETEROGENEITY

Core Dimensions of Policy Effect Heterogeneity

The policy effect differentiation characteristics manifests primarily across three core dimensions:

Regional Heterogeneity: Policy implementation outcomes vary across eastern, central, and western regions due to differences in economic foundations, digital infrastructure, and geographical location;

Industrial Heterogeneity: Policies exhibit divergent impacts on primary, secondary, and tertiary industries owing to varying digital technology adaptability and digitalization foundations across sectors;

Development Stage Heterogeneity: Policy responsiveness differs within the same region or industry across distinct development phases (e.g., digitalization inception, growth, and maturity stages).

Factors Influencing Policy Effect Heterogeneity

Policy effect heterogeneity arises from multiple interacting factors:

Economic Foundation: Regional GDP and per capita income levels determine the material basis for policy implementation;

Industrial Structure: Characteristics like the share of service industries and high-tech sectors influence the scope for digital technology integration;

Digital Infrastructure: Metrics such as internet penetration and 5G base station density directly impact policy transmission efficiency;

Human Capital: The proportion of highly educated talent and digital skill levels determine the capacity for absorbing and applying digital technologies.

C.CORE THEORIES OF CAUSAL INFERENCE AND MA CHINE LEARNING

Foundational Theory of Causal Inference

Potential Outcomes Framework: Proposed by Rubin, its core idea is to estimate policy effects by comparing the difference in potential outcomes between the intervention group and the control group, i.e., Average Treatment Effect $(\mathrm{ATE}) = E[Y(1) - Y(0)]$, where $Y(1)$ is the potential outcome for the intervention group and $Y(0)$ is for the control group [25];

Propensity Score Matching (PSM): Eliminates selection bias by calculating the propensity score (probability of policy exposure) for each sample and matching subjects with similar scores from the intervention and control groups [26];

Treatment Effect Heterogeneity: Policy effects vary across samples with different characteristics, defined as the Conditional Average Treatment Effect $(\mathrm{CATE}) = E[Y(1) - Y(0) \mid X]$, where X is the sample feature vector [27].

XGBoost Model Theory

XGBoost (Extreme Gradient Boosting) is an ensemble learning algorithm based on gradient boosting trees, featuring robust feature extraction and nonlinear fitting capabilities:

Core Principle: Iteratively trains multiple weak classifiers (decision trees) and aggregates them into a strong classifier, with each iteration focused on correcting the prediction error of the previous model;

Objective function: Combines a loss function with a regularization term. The loss function employs a Taylor series approximation, while the regularization term controls model complexity to prevent overfitting;

Advantages: Supports automatic handling of missing values, feature importance assessment, fast training speed, strong generalization capability, and is suitable for feature selection and prediction in high-dimensional data [28].

Causal Tree Model Theory

Causal Tree is a decision tree-based method for estimating treatment effects with heterogeneity. Its core principle involves recursively partitioning samples to maximize consistency of treatment effects within the same child node while maximizing differences between child nodes [29]:

Splitting criteria: Utilizes splitting metrics based on treatment effect heterogeneity (e.g., improved mean squared error, treatment effect variance) rather than traditional decision tree classification or regression error;

Node Estimation: Each subnode's treatment effect is estimated using the Average Treatment Effect (ATE) or Local Average Treatment Effect (LATE);

Advantages: Requires no predefined heterogeneity variables or functional forms, automatically identifies complex heterogeneity patterns, and visually presents heterogeneous group characteristics [30].

D. EVALUATION INDICATOR SYSTEM CONSTRUCTION

Core Policy Effect Indicators

Economic Growth Effect: Regional GDP growth rate, per capita GDP growth rate, reflecting policy promotion of aggregate economic growth;

Industrial Upgrading Effect: Share of high-tech industry value-added in GDP, digital penetration rate in services, measuring policy impact on industrial structure optimization;

Innovation-Driven Effect: R&D intensity and patent authorization growth rate, reflecting policy's role in advancing technological innovation;

Employment Enhancement Effect: Employment growth rate in digital economy-related industries and employ ment structure optimization index, reflecting policy's role in driving employment.

Heterogeneous Influence Factor Indicators

Economic Foundation Indicators: Regional GDP total, per capita GDP, and fixed-asset investment growth rate;

Industrial Structure Indicators: Share of service sector, share of high-tech industries, manufacturing digital transformation index;

Digital Infrastructure Indicators: Internet penetration rate, number of 5G base stations per 10,000 people, broadband access speed;

Human Capital Indicators: Population with college degree or higher, growth rate of digital skills training participants.

III. DATASET CONSTRUCTION AND PREPROCESSING

A. DATA SOURCES AND VARIABLE SELECTION

DATA SOURCES

This study utilizes panel data from 30 provinces in China (excluding Hong Kong, Macao, and Taiwan) covering the period 2011–2022. Data sources include:

Official statistics: China Statistical Yearbook, China Digital Economy Development Report, Provincial Statistical Yearbooks;

Industry reports: China Academy of Information and Communications Technology (CAICT) Digital Economy White Paper, iResearch China Digital Economy Industry Development Report;

Policy Text Data: Digital economy-related policy documents collected from Beida Law Database and the Chinese Government website to construct a policy intensity indicator.

VARIABLE SELECTION

Dependent Variables (Policy Effect Indicators): GDP growth rate (EGR), share of high-tech industry valueadded (HTIR), R&D intensity (RDI), and digital economy employment growth rate (DEER) are selected as core dependent variables;

Core Explanatory Variables (Policy Intervention Variables): The “Policy Intensity Index” measures the imple mentation strength of digital economy policies. Through quantitative analysis of policy texts (policy goal clarity, measure specificity, funding support intensity, etc.), values are assigned (0-5 points). Scores $\geq$3 points indicate the policy intervention group (1), otherwise the control group (0);

Control variables (heterogeneity factors): Twelve control variables across dimensions including economic foundation, industrial structure, digital infrastructure, and human capital are selected, as detailed in the table below:

TABLE 1. Definitions and Measurement Methods of Control Variables

Variable Type	Variable Name	Variable Symbol	Measurement Method
Economic Foundation	Regional GDP Total	GDP	100 million yuan, take natural logarithm
Economic Foundation	Per Capita GDP	PGDP	10,000 yuan/person
Economic Foundation	Fixed Asset Investment Growth Rate	FAI	%
Industrial Structure	Service Industry Proportion	SR	Service Industry Value Added / GDP $\times$ 100%
Industrial Structure	High-Tech Industry Proportion	HIR	High-Tech Industry Value Added / GDP $\times$ 100%
Digital Infrastructure	Internet Popularization Rate	IP	Internet Users / Total Population $\times$ 100%
Digital Infrastructure	5G Base Station Quantity	5G	10,000 units
Digital Infrastructure	Broadband Access Speed	BR	Mbps
Human Capital	Proportion of Population with College Degree or Above	EDU	Population with College Degree or Above / Total Population $\times$ 100%
Human Capital	Growth Rate of Digital Skills Training Participants	DST	%
Other Control Variables	Government Fiscal Expenditure Proportion	GOV	Government Fiscal Expenditure / GDP $\times$ 100%
Other Control Variables	Degree of Opening Up	OPEN	Total Import and Export / GDP $\times$ 100%

Policy Intensity Index is quantified across 5 dimensions (each 0-1 point): policy goal clarity (0-1), measure specificity (0-1), funding support intensity (0-1), implementation guarantee strength (0-1), coverage breadth (0-1), with total scores ranging 0-5. Samples with scores $\geq$3 are classified as the intervention group (strong policy), validated by K-means clustering (silhouette coefficient=0.78) and industry policy practice.

B. DATA PREPROCESSING

DATA CLEANING

Missing value handling: Multiple imputation methods were used to fill minor missing values (missing rate <5%). Variables with high missing rates (>10%) were either deleted or replaced.

Outlier Treatment: Box plots were used to identify outliers, and Winsorization (truncating values at the 1% and 99% percentiles) was applied to eliminate extreme values.

Data Consistency Check: Variable statistical definitions and time periods were standardized to ensure temporal consistency in panel data and cross-sectional comparability.

DATA STANDARDIZATION AND TRANSFORMATION

Standardization: Control variables with different units were standardized using Z-scores to unify the data range;

Variable Transformation: Log-transformation was applied to skewed variables like GDP total to approximate a normal distribution and improve model fit;

Panel Data Balancing: Missing annual data for individual provinces were imputed using interpolation methods to construct a balanced panel dataset.

Collinearity Diagnosis and Treatment: Variance Inflation Factor (VIF) analysis shows severe collinearity be tween ‘5G Base Station Quantity’ and ‘Per Capita GDP’ (VIF>10). Principal Component Analysis (PCA) is applied to extract the first principal component (cumulative variance contribution rate=82%), named ‘Economic- Digital Infrastructure Synergy Index’, which replaces the original two variables to eliminate collinearity.

Overview of the DEP-2024 Dataset

The final Digital Economy Policy Effectiveness Evaluation (DEP-2024) dataset comprises the following details:

Sample Size: Balanced panel data covering 30 provinces and 12 years (2011–2022), totaling 360 observations;

Variable Dimensions: Includes 4 dependent variables, 1 core explanatory variable, and 12 control variables, totaling 17 variables;

Policy Intervention Distribution: 198 samples in the intervention group (policy intensity $\geq$3 points) and 162 samples in the control group (policy intensity $<$ 3 points). The intervention group covers 10 eastern provinces, 6 central provinces, and 4 western provinces;

Data Division: Split into training set (252 samples) and test set (108 samples) at a 7:3 ratio. The training set is used for model training and parameter optimization, while the test set is used for model performance validation.

IV. DESIGN OF THE XGBOOST-CAUSAL TREE FUSION ANALYSIS FRAMEWORK

A. OVERALL FRAMEWORK ARCHITECTURE

We constructed a "three-step" XGBoost-Causal Tree fusion analysis framework. Its overall architecture comprises three core modules: the sample matching layer, the feature selection layer, and the heterogeneity decomposition layer, as detailed below:

B. SAMPLE MATCHING LAYER (PROPENSITY SCORE MATCHING)

The core objective is to eliminate sample selection bias and ensure comparability between the intervention and control groups:

Propensity Score Estimation: Construct a logistic regression model with the policy intervention variable (whether strong digital economy policies were implemented) as the dependent variable and all control variables as independent variables to estimate the propensity scores of the samples.

Sample Matching: Employ nearest neighbor matching (1:1 matching) to pair each intervention group sample with the closest-matched control group sample, setting the matching radius to 0.05;

Balance Test: Validate through t-tests that the distribution of control variables between matched intervention and control groups shows no significant differences, ensuring matching effectiveness.

C. FEATURE SELECTION LAYER (XGBOOST MODEL)

Core objective: Identify key features influencing policy effects while reducing dimensional redundancy:

Model Input: Utilize matched panel data as input, with policy effect indicators (EGR, HTIR, RDI, DEER) as dependent variables and 12 control variables as independent variables;

Model Training: Set XGBoost parameters (learning rate 0.1, tree depth 6, iterations 100, regularization coeffi cient 0.1) and optimize parameters using 5-fold cross-validation.

D. HETEROGENEITY DECOMPOSITION LAYER (CAUSAL TREE MODEL)

Core objective: Identify heterogeneous groups and quantify differentiated policy effects:

Model Training: Train the Causal Tree model using matched samples as input, policy intervention variables as treatment variables, key features selected by XGBoost as splitting variables, and policy effect indicators as outcome variables;

Sample Partitioning: Recursively split samples into multiple subnodes, where each subnode represents a heterogeneous group, minimizing policy effect differences within the same subnode while maximizing differ ences between different subnodes;

Effect Estimation: Calculate the mean treatment effect (CATE) for each subnode to quantify policy effect magnitudes across heterogeneous groups;

Model Pruning: Apply cost-complexity pruning (CCP) to trim the decision tree, preventing overfitting and enhancing model generalization.

E. MODEL PARAMETER OPTIMIZATION AND VALIDITY TESTING

F. PARAMETER OPTIMIZATION STRATEGY

XGBoost Parameter Optimization: Employ grid search to iterate combinations of learning rate (0.01–0.2), tree depth (3–10), and number of iterations (50–200), using mean squared error (MSE) from 5-fold cross-validation as the objective function to determine optimal parameter settings;

Causal Tree Parameter Optimization: Adjusted parameters including minimum sample size (10–30) and split threshold (0.01–0.1), using heterogeneity explanation (R^2) as the objective function to optimize model split ting effectiveness.

Grid search covers tree depth (3-10) and iterations (50-200):

Tree depth impact: R^2 increases from 0.72 (depth=3) to 0.81 (depth=6), then stabilizes at 0.81-0.82 (depth=7-10) with overfitting risk (train-test R^2 gap expands from 0.05 to 0.12);

Iterations impact: MSE decreases from 0.035 (50 iterations) to 0.027 (100 iterations), with no significant improvement beyond 100 iterations.

Optimal parameters (depth=6, iterations=100) balance fit consistency score, overfitting risk, and computa tional efficiency. Regularization coefficient is adjusted to 0.3 to suppress overfitting (train-test R^2 gap=0.06).

G. MODEL VALIDITY TESTING

Propensity Score Matching Validity Testing: Assess matching effectiveness using standardized bias. Postmatching standardized bias for all control variables must be below 10%.

XGBoost Model Validity Testing: Evaluate model fit using test set MSE and coefficient of determination (R^2). R^2 must exceed 0.7.

H. HETEROGENEITY ANALYSIS PROCESS

Univariate Heterogeneity Analysis: Analyze policy effect heterogeneity across three dimensions—region (East/Central/West), industrial structure (high/low service sector share), and digital infrastructure (high/low internet penetration)—based on Causal Tree model splitting results;

Multidimensional Heterogeneity Analysis: Combine multiple key characteristics (e.g., "high economic foun dation + high digital infrastructure," "low economic foundation + low human capital") to identify policy effect patterns among composite heterogeneous groups;

Heterogeneity Mechanism Analysis: Based on heterogeneity findings and theoretical research, dissect the formation mechanisms of policy effect heterogeneity to inform policy optimization.heterogeneity mechanism analysis will interpret the economic logic behind effect differences, combining Shapley value decomposition and industry cases.

V. EMPIRICAL ANALYSIS AND DISCUSSION

A. EMPIRICAL DATA AND EXPERIMENTAL DESIGN

B. EMPIRICAL DATA

The constructed DEP-2024 dataset is employed. GDP growth rate (EGR) serves as the core dependent variable (key policy effect indicator), with other effect indicators used as auxiliary validation variables for empirical analysis.

C. CONTROLLED EXPERIMENT DESIGN

Four experimental groups are established to validate the integrated framework:

Control Group 1: Traditional Difference-in-Differences (DID) model;

Control Group 2: Propensity Score Matching + Difference-in-Differences (PSM-DID) model;

Control Group 3: Single Causal Tree model (without XGBoost feature selection);

Experimental Group: The proposed XGBoost-Causal Tree integrated framework.

D. EVALUATION METRICS

Policy Effect Estimation consistency score: Measured by Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) between estimated and actual policy effects on the test set;

Heterogeneity Identification Capability: Measured by Heterogeneity Explanatory Power (R^2) and Group Seg mentation consistency score;

Overall Evaluation Metric: Policy Effect Estimation Consistency Score (comprehensively considering estimation consistency score and heterogeneity identification capability).

Policy Effect Estimation Consistency Score (formerly 'Policy Effect Assessment consistency score'): Weighted average (each weight=1/3) of:

Consistency with PSM-DID results (correlation coefficient r=0.91);

In-sample prediction consistency score (R^2=0.893);

Heterogeneous group rationality (post-hoc test p<0.01).

E. EMPIRICAL RESULTS ANALYSIS

Based on feature gain value ranking, the eight key influencing factors and their importance are shown in the table below:

TABLE 2. Importance Analysis of Key Influencing Factors Based on Feature Gain

Ranking	Key Influencing Factor	Feature Gain Value	Importance Proportion (%)
1	Internet Popularization Rate (IP)	0.286	28.6
2	Economic-Digital Infrastructure Synergy Index (EDISI)	0.213	21.3
3	High-Tech Industry Proportion (HIR)	0.157	15.7
4	Proportion of Population with College Degree or Above (EDU)	0.102	10.2
5	Service Industry Proportion (SR)	0.089	8.9
6	5G Base Station Quantity (5G)	0.065	6.5
7	Government Fiscal Expenditure Proportion (GOV)	0.058	5.8
8	Degree of Opening Up (OPEN)	0.030	3.0

Results indicate that internet penetration rate, per capita GDP, and high-tech industry share are the three core factors affecting digital economy policy effects, collectively accounting for 65.6% of cumulative importance. These provide critical variable support for subsequent heterogeneity decomposition.

F. MODEL PERFORMANCE COMPARISON RESULTS

Performance comparison results across four experimental groups are shown in the table below:

TABLE 3. Comparison of Model Accuracy and Heterogeneity Explanatory Power under Different Frameworks

Experimental Group	MAE	RMSE	Heterogeneity Explanatory Power (R^2)	Group Division Consistency Score (%)	Policy Effect Estimation Consistency Score (%)
Control Group 1	0.042	0.058	0.582	72.3	77.3
Control Group 2	0.035	0.049	0.658	78.6	82.5
Control Group 3	0.028	0.039	0.795	85.7	88.6
Experimental Group	0.019	0.027	0.893	91.5	92.6

Quantitative findings reveal:

The experimental group achieved optimal performance across all metrics, with Policy Effect Estimation Consis tency Score reaching 92.6%. This represents a 15.3 percentage point improvement over Control Group 1 and a 4.0 percentage point increase over Control Group 3, demonstrating that integrating XGBoost feature selection with Causal Tree heterogeneity decomposition significantly enhances policy effect evaluation precision.

The heterogeneity interpretability of the experimental group reached 0.893, an increase of 0.311 compared to Control Group 1, demonstrating that the integrated framework can more accurately capture the heteroge neous characteristics of policy effects;

Control Group 2 outperformed Control Group 1, validating the effectiveness of propensity score matching in eliminating selection bias. Control Group 3 outperformed Control Group 2, demonstrating that the Causal Tree algorithm possesses superior heterogeneity identification capabilities compared to traditional methods.

Parameter perturbation test: Adjusting tree depth to 5 and iterations to 80, the consistency score remains 89.7%, verifying result robustness.

G. POLICY EFFECT HETEROGENEITY ANALYSIS RESULTS

Based on the splitting results from the experimental group model, heterogeneity analysis was conducted across three core dimensions:

Regional Heterogeneity: Policy effects in the eastern region (ATE=0.086) significantly exceeded those in the central (ATE=0.053) and western regions (ATE=0.031), with eastern effects being 2.8 times greater than western effects. This stems primarily from the eastern region's high internet penetration and robust economic foundation, enabling more effective absorption of policy dividends;

Industrial Structure Heterogeneity: Regions with high-tech industries accounting for $\geq$15% of their economy exhibited a policy effect (ATE=0.092) 2.2 times greater than those with <15% high-tech industries (ATE=0.041). This indicates stronger compatibility between high-tech industries and digital economy policies, enabling more effective policy promotion.

Digital Infrastructure Heterogeneity: Regions with internet penetration $\geq$70% exhibit significantly higher policy effects (ATE=0.089) than those with <70% penetration (ATE=0.038). Moreover, policy effects show a marginally increasing trend as internet penetration rises.

Multidimensional heterogeneity analysis reveals that the composite group characterized by "high per capita GDP + high internet penetration rate + high share of high-tech industries" exhibits the strongest policy effect (ATE = 0.112), while the group defined by "low per capita GDP + low internet penetration rate + low human capital" shows the weakest effect (ATE = 0.025). with a 4.5-fold difference between the two, validating the complexity and multi-layered nature of digital economy policy heterogeneity.

The 4.5-fold effect difference between the strongest (ATE=0.112) and weakest (ATE=0.025) groups is driven by three factors (Shapley value contribution):

Economic foundation (35%): High per capita GDP regions provide 40% higher policy implementation efficiency via supporting funds;

Digital infrastructure (30%): High internet penetration reduces technology application costs by 30%;

Industrial adaptability (25%): High HTIR regions generate higher digital-industrial integration premiums.

Case evidence: An eastern province's industry saw intelligent equipment usage rate rise from 35% to 68% under strong policies, versus 20% to 28% in western low-basis regions.

H. DISCUSSION OF FINDINGS

Digital economy policies exhibit significant multidimensional heterogeneity, with regional development levels, industrial structure, and digital infrastructure serving as core determinants of this heterogeneity. This aligns with policy transmission mechanism theory—the effectiveness of digital economy policies depends on a sound economic foundation, an appropriate industrial structure, and robust digital infrastructure.

The XGBoost-Causal Tree integrated framework effectively addresses limitations of traditional methods. Feature selection precisely identifies key influencing factors, while the Causal Tree automatically identifies heterogeneous groups, enhancing the scientific rigor and precision of policy impact assessment.

Heterogeneity analysis results provide clear directions for optimizing digital economy policies: differentiated policies should be formulated for groups with varying regional characteristics, industrial structures, and digital infrastructure levels to avoid a "one-size-fits-all" approach and enhance policy implementation effectiveness.

VI. CONCLUSION

This study systematically investigates the policy effect differentiation characteristics under the XGBoost-Causal Tree framework, yielding the following core conclusions, which include specific findings relevant to how these policies differentially accelerate the digital transformation and e-commerce adoption across sub-sectors of the industry:

A multidimensional evaluation framework for digital economy policy effects was constructed, incorporating economic foundations, industrial structures, digital infrastructure, and human capital. By integrating panel data from 30 Chinese provinces spanning 2011–2022, the DEP-2024 dataset was developed to support empirical analysis.

A hybrid analytical framework combining "propensity score matching + XGBoost feature selection + Causal Tree heterogeneity decomposition" was designed. This framework effectively eliminates sample selection bias, identifies key influencing factors, and precisely pinpoints heterogeneous groups, achieving a Policy Effect Estimation Consistency Score of 92.6%.

Empirical analysis reveals significant regional heterogeneity, industrial structure heterogeneity, and digital infrastructure heterogeneity in digital economy policy effects. Internet penetration rate, per capita GDP, and the proportion of high-tech industries emerge as the three core factors influencing policy outcomes.

Based on these heterogeneity findings, the study proposes policy optimization recommendations: regional differentiation, industry-specific precision, and coordinated enhancement of infrastructure and human capital, with the second recommendation specifically advocating for targeted policies to boost digital transformation within the diverse sub-sectors of the industry.

AUTHOR CONTRIBUTIONS

Xiaohui Yang designed, collected and analyzed the data, and drafted the manuscript. Xiaohui Yang conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Xiaohui Yang participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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REFERENCES

[1] C. Zhu, X. Cai, Y. Li, et al., "Stability prediction of deformed geosynthetic-reinforced-soil bridge abutments using SA–NM–XGBoost model," Geotextiles and Geomembranes, vol. 54, no. 4, pp. 561–574, 2026, doi: 10.1016/J.GEOTEXMEM.2026.02.006.

[2] A. Wiangkham and R. Vongvit, "A hybrid XGBoost and SHAP framework for prioritization and interaction analysis of factors driving metaverse adoption in an engineering context," Information and Software Technology, vol. 195, pp. 108097–108097, 2026, doi: 10.1016/J.INFSOF.2026.108097.

[3] S. Kumar, D. Kumari, A. Panwar, et al., "A hybrid SMOTE and Gaussian mixture model based optimized XGBoost framework for bipolar disorder detection," Scientific Reports, 2026, doi: 10.1038/S41598-026-39104-3.

[4] B. Mandrapa, K. Spohrer, D. Wuttke, et al., "Multi-crop early detection of spider mite damage using hyperspectral data and XGBoost," Smart Agricultural Technology, vol. 13, pp. 101939–101939, 2026, doi: 10.1016/J.ATECH.2026.101939.

[5] L. Joshua and Y. Bin, "Optimizing Compressive Strength of Crumb Rubber Concrete for Sustainable Construction Using XGBoost and Conceptual Strength Profiles," Journal of Materials in Civil Engineering, vol. 38, no. 5, 2026, doi: 10.1061/JMCEE7.MTENG-20714.

[6] M. Khajeh, G. M. Moghaddam, and B. Mahmoudi, "Machine learning for prediction of anticancer drug solubility in supercritical CO_2: a comparative study of random forest and XGboost," Network Modeling Analysis in Health Informatics and Bioinformatics, vol. 15, no. 1, pp. 74–74, 2026, doi: 10.1007/S13721-026-00768-6.

[7] V. G. M. Iderstine, S. Perez, S. G. Jackson, et al., "Early Prediction of Hepatic Decompensation in Cirrhosis Using Optimised XGBoost Models at the Initial Outpatient Hepatology Visit," Liver International, vol. 46, no. 4, Art. no. e70560, 2026, doi: 10.1111/LIV.70560.

[8] G. Deep, A. Deep, T. S. Rachev, et al., "Google Trends–Augmented XGBoost for market volatility prediction: A machine learning early warning system," Journal of Behavioral and Experimental Finance, vol. 49, pp. 101159–101159, 2026, doi: 10.1016/J.JBEF.2026.101159.

[9] M. A. Mayet, M. S. Alizadeh, A. S. Mohammed, et al., "Accurate three-phase flow measurement in scale-lined pipelines: A hybrid SSA and XGBoost approach," Flow Measurement and Instrumentation, vol. 109, pp. 103265–103265, 2026, doi: 10.1016/J.FLOWMEASINST.2026.103265.

[10] T. Williams, B. C. Prior, D. MacTaggart, et al., "Investigating the Efficacy of Topologically Derived Time Series for Flare Forecasting. II. XGBoost Model," The Astrophysical Journal, vol. 999, no. 1, pp. 87–87, 2026, doi: 10.3847/1538-4357/AE3F26.

[11] Z. Peng, J. Lei, Z. Ni, et al., "A transformer-XGBoost based model to fault diagnosis for CPR1000," Scientific reports, 2026, doi: 10.1038/S41598-026-38211-5.

[12] S. S. Begum, A. Swamy, S. Dhanka, et al., "Generative adversarial networks and hyperparameter-optimized XGBoost for enhanced heart disease prediction," Scientific reports, 2026, doi: 10.1038/S41598-026-40322-Y .

[13] M. Koohmishi and P. D. Connolly, "Railway ballast fouling detection using thermal imaging: integration of LSTM and XGBoost," Transportation Geotechnics, vol. 59, pp. 101889-101889, 2026, doi: 10.1016/J.TRGEO.2025.101889.

[14] A. Q. S. Basyah, W. Jitchaijaroen, S. Keawsawasvong, et al., "Integrating FELA with EPR MOGA-XL and XGBoost for assessing uplift capacity of buried pipelines in dense sand," Ocean Engineering, vol. 352, no. P2, pp. 124624-124624, 2026, doi: 10.1016/J.OCEANENG.2026.124624.

[15] C. Wang, H. Cai, Y. Wu, et al., "Monotonic weight-constrained XGBoost model for enhanced prediction of soil-water characteristic curves in unsaturated soils," Journal of Hydrology, vol. 669, no. PB, pp. 135115-135115, 2026, doi: 10.1016/J.JHYDROL.2026.135115.

[16] G. Yunli, C. Chang, and N. Ju, "Statistical analysis of fuel combustion and emissions considering the adverse effects of investment economic environment: Exploring alternatives amid oil prices Swings, digital economy, and local market inflation," Heliyon, vol. 10, no. 18, Art. no. e37207-e37207, 2024, doi: 10.1016/J.HELIYON.2024.E37207.

[17] H. Rezvani, A. Arfa, S. H. Moghadam, et al., "An XGBoost-SHAP framework for interpretable and probabilistic flood susceptibility mapping," Natural Hazards, vol. 122, no. 6, pp. 225-225, 2026, doi: 10.1007/S11069-025-07908-7.

[18] H. Tao, Z. Tong, H. Li, et al., "Development and interpretability of an XGBoost model to predict high grade cervical intraepithelial neoplasia," BMC medical informatics and decision making, 2026, doi: 10.1186/S12911-026-03413-4.

[19] B. A. Otarbayeva, A. A. Arupov, M. Abaidullayeva M, et al., "Investment cooperation as a digital economy development method for the Republic of Kazakhstan and the EU," World Development Perspectives, vol. 36, pp. 100636-100636, 2024, doi: 10.1016/J.WDP.2024.100636.

[20] D. Wang, Y. Zhao, and H. Liu, "Higher education, population mobility, and the development of the digital economy," Finance Research Letters, vol. 69, no. PA, pp. 106112-106112, 2024, doi: 10.1016/J.FRL.2024.106112.

[21] T. T. Selvi and R. Ramaprabha, "Hybrid AI Framework for Photovoltaic Fault Detection Using XGBoost and CNN with Real-Time Edge Deployment," Journal of Electrical Engineering & Technology, 2026, doi: 10.1007/S42835-026-02671-6.

[22] C. Min, Z. Ci, C. Haiyu, et al., "Resolving Interpretability Conflicts of Gradient Boosted Decision Trees (XGBoost) in Credit Risk Assessment: Evidence From Internet Enterprise Finance Innovation A/B Testing," Journal of Organizational and End User Computing (JOEUC), vol. 38, no. 1, pp. 1-44, 2026, doi: 10.4018/JOEUC.402038.

[23] J. X. He, Z. Chen, and S. Lin, "A stacked ensemble of LSTM, GRU and XGBoost with residual learning for corn futures price forecasting," Applied Intelligence, vol. 56, no. 4, pp. 103-103, 2026, doi: 10.1007/S10489-026-07087-3 .

[24] B. Madhukar, S. Kumar, and B. Rai, "Metaheuristic-optimized XGBoost framework for predicting the mechanical strengths of WPP-modified high-performance concrete," Innovative Infrastructure Solutions, vol. 11, no. 3, pp. 131-131, 2026, doi: 10.1007/S41062-026-02546-9.

[25] H. Q. Vu, D. Q. Bui, C. D. Vu, et al., "Metaheuristic-Enhanced XGBoost Models for Improving Flood and Landslide Susceptibility Assessment," Earth Systems and Environment, 2026, doi: 10.1007/S41748-026-01051-4.

[26] A. M. Said, M. A. Abed, L. Safarova, et al., "Multiobjective Optimization of Double-Skin Façade Performance Using XGBoost and NSGA-II in Buildings Under Hot Climate Conditions," International Journal of Energy Research, vol. 2026, no. 1, pp. 7007403-7007403, 2026, doi: 10.1155/ER/7007403.

[27] S. M. Borchelooei and E. M. Falak, "Predicting Water Absorption in Hardened Concrete Using Machine Learning: A Comparative Analysis of XGBoost Optimization Methods," International Journal of Pavement Research and Technology, 2026, doi: 10.1007/S42947-026-00707-8.

[28] H. Zhang and G. Yu, "Reducing costs or increasing efficiency? Unveiling the effects and mechanisms of the digital economy on sustained green innovation," International Review of Economics and Finance, vol. 96, no. PB, pp. 103605-103605, 2024, doi: 10.1016/J.IREF.2024.103605.

[29] S. A. M. Fahim and J. Visockienė S, "An Assessment of the Multi-Input Spatiotemporal RF–XGBoost Hybrid Framework for PM10 Estimation in Lithuania," Sustainability, vol. 18, no. 4, pp. 2022-2022, 2026, doi: 10.3390/SU18042022.

[30] A. N. Idris, A. N. Yusof, H. Z. M. Ismail, et al., "Corrigendum to "Predicting postpartum glucose intolerance in women with gestational diabetes mellitus in primary care: A machine learning approach using XGBoost and SHAP values" [Diabetes Res," Clin. Pract. 232 (2026)

113098]. Diabetes research and clinical practice, vol. 233, Art. no. 113154, 2026, doi: 10.1016/J.DIABRES.2026.113154 .