Journal of Trends in Financial and Economics
ISSN: 3007-696X
DOI: https://doi.org/10.61784/jtfe3053

MACHINE LEARNING-DRIVEN GOVERNANCE: PREDICTING THE EFFECTIVENESS OF INTERNATIONAL TRADE POLICIES THROUGH POLICY AND GOVERNANCE ANALYTICS

Emran Hossain*, Kamal Pasha Shital, Md Shihab Rahman, Safiul Islam, Sajidul Islam Khan, Abdullah Al Mahmud Ashik
College of Graduate and Professional Studies, Trine University, Angola, Indiana, USA.
Corresponding Author: Emran Hossain, Email: ehossain24@my.trine.edu

Abstract: Since global trade is becoming more complicated, policymakers are relying on more advanced tools to predict, analyze, and decide. Thanks to machine learning (ML), predictive governance could change the way international trade policies are evaluated and shaped by adding more accuracy and speed. At present, it is estimated that 80% of major economies use data-driven analytics in some part of setting their trade policies. Meanwhile, the use of artificial intelligence in government is expected to reach $3.7 billion by the year 2027 with a growth rate of 34.5% annually. This study uses ML algorithms including time-series forecasting, regression analysis, and natural language processing in the analysis and prediction of the outcomes of international trade policies. The analysis draws from datasets covering over 70 countries and data on trading activities over 20 years to see the results of applying ML techniques to different trade policies. From the analysis, we can confirm that ML models improve policy outcome prediction accuracy by up to 25% more than using traditional econometric models. Besides, it becomes apparent from feature importance analysis that changes in the GDP, happenings at the world stage, and commodity prices influence and shape trade patterns. The statistics confirm how predictive governance is useful for tracking recent developments, limiting the effects of risks, and helping design quick policy responses in international trade. Lastly, the paper suggests how to apply machine learning in government and international organizations by dealing with data quality, transparency, and considering ethical concerns.
Keywords: Data-driven analytics; Machine learning; Policy analysis; International trade

1 INTRODUCTION

Because the world is now strongly influenced by quick globalization, unpredictable markets, and technological developments, foreign trade plays a big role in growing economies and creates various policy issues. Despite growth in global trade of 2.7%, the WTO explained that merchandise trade was stifled by a variety of difficulties like geopolitical risks, unstable commodity prices, and efforts to recover from the pandemic [1]. Such factors prove that we need to use more flexible and information-based methods for handling and judging trade policies. Today, governments and international organizations are using advanced tools for data analysis and predictions to help them with decision-making. What makes this approach special is machine learning (ML), which belongs to artificial intelligence and helps computers look for trends in large sets of information. Trade policy applications help with multi-dimensional data on GDP, tariffs, shipping expenses, and news about international sentiments to give useful results at any time. According to the statistics from 2023 about three out of every four G20 member countries have already used or tested machine learning systems in various economic policy assessments [2]. Many points about trade policy have been revealed by econometric methods, yet there are clear weaknesses in such methods. Since these models are linear, only allow limited interaction, and rely on the past, they find it hard to keep up with today's world. In the opposite way, supervised and unsupervised learning, NLP, and deep learning in ML help to handle complex data interactions and make quick changes to updated information. It has been found that artificial intelligence models can detect changes in markets and government rules faster than usual approaches [1, 3].

Policies on trade can shape a country's economy, the employment of a tremendous number of people, the stability of supply networks, and the way countries get along globally. The World Bank believes that using analytics in trade policies could boost the GDP of the world by $600 billion by the year 2030 [4]. Experts believe that since global trade is becoming more and more complex, integrating machine learning into policy work is becoming increasingly important. It means that governments and international organizations are now viewing and making trade policy differently. Predictive governance is different from the usual reactive approach because it involves looking ahead, acting early, and using data at every step of operation. Since international supply issues and sudden market events can interrupt many areas, having the ability to predict and respond is very important. From a survey carried out by the International Chamber of Commerce in 2023, it was revealed that 78% of policymakers expect advanced analytics and machine learning to greatly benefit trade policy over the next five years [5-6]. Using prediction tools, governments can detect first signs of economic trouble, check the results of policy decisions, and guarantee that trade deals aim for sustainable growth. It looks like we are moving from making policies based on intuition to decisions driven mainly by analyzing data [2].

Machine learning works well with the many aspects of international trade. ML gathers important facts and insights from vast sources of data by making use of techniques such as regression analysis, classification, clustering, and natural language processing. It makes it possible to detect interesting trends, the reasons behind them [6], and patterns linked to things that conventional econometrics methods usually hide. By analyzing a lot of data from the past, supervised ML models are good at predicting trade tariff results, and unsupervised ML models can identify countries with comparable trade styles to help in bargaining Rochemel. More access to high-frequency data and advances in cloud technology have promoted the increased use of ML when making policy judgments. For this reason, ML helps policymakers make wiser and faster choices because the insights are always up to date [7-9].
Today, when the world is unpredictable, policies made with wrong or missing information often end up costing a lot. With data, leaders can predict various outcomes, identify hazards, and choose the best strategies for desired effects. According to the IMF, industries that make use of data-driven trading policies can achieve, on average, a 12% uplift in their exports if compared to those with traditional approaches [10]. Besides, setting up ML-based analytics helps trade policies keep up with sudden changes in commodity prices, finding new trading partners, or the start of a geopolitical conflict. Data has become more necessary now for policymakers who aim to make the economy stable and help everyone prosper. The aim of this study is to merge principles of emerging machine learning with the requirements of those making international trade policies. Combining a thorough analysis of current papers, facts from research, and case studies, we investigate how predictive governance can change the global trade sector.

2 LITERATURE REVIEW

In the past few decades, the method used to evaluate international trade policies has changed, moving from using theories mainly to using more data and computations. As more countries are involved in trade and exchanges, and as a lot more data becomes accessible, policy experts are now looking for new methods to stand and anticipate the effects of trade interventions. Even though conventional models are valuable, it has become well known that they do not do well with complex, changing, and real-time data. Machine learning (ML) has made it possible to use predictive governance with more detailed analysis of different datasets and find patterns that were not known before [1, 2, 11]. Although technology is advancing swiftly, taking time to review traditional and modern approaches is very important. The literature review brings important developments together, checks the advantages and disadvantages of various methods, and notes the areas that remain unresolved by previous research.

2.1 Historical Approaches to International Trade Policy Evaluation

For a long time, trade policy evaluation has depended on classical economic ideas and econometric methods. Distance, the strength of economies, and resources were first quantitatively explained in their impacts on international trade with the help of the Gravity Model and the Heckscher-Ohlin Model. During the late 20th century, people started to rely on Computable General Equilibrium (CGE) models to explore how different trade policies influence various sectors of different economies [1, 11]. Although they are built on solid theories, such models usually expect a straight-line pattern, constant elasticity, and rationale in people's decisions [2]. Such companies have problems dealing with the fast changes in the world economy, import barriers, and interruptions in their supply chains. In addition, how much data they use and how complicated they have prevented their regular use in live policy evaluation.

2.2 Traditional vs. Data-Driven Predictive Methods

Because trade data and computer processing are more accessible than before, people can easily identify the problems faced by traditional economic modeling (Table 1). Although good for planned scientific experiments, these models encounter problems when dealing with a lot of information and non-straight patterns in trade. In comparison, methods based on machine learning are created to discover difficult patterns and linkages that are not easily identified by other means [11]. Several studies have found that using machine learning in trade data or tariff analysis can enhance accuracy by anything between 15% and 30% more than traditional methods. This has made the World Bank and OECD spend more on using statistical modeling and other tools for monitoring trade and making future.

Table 1 Comparison of Traditional vs. Machine Learning Methods for Trade Policy Evaluation

Method	Strengths	Weaknesses	Example Use Case
Traditional Econometric Models (e.g., OLS, CGE)	Grounded in economic theory- Transparent and explainable	Struggle with complex, high-dimensional, or non-linear data- Less adaptive to new trends- Require strong assumptions	Estimating impact of tariff changes using OLS regression
Machine Learning Models (e.g., Random Forests, LSTM, NLP)	Handle large/complex datasets- Capture non-linear patterns- Adaptive and updateable- Incorporate diverse features (text, sentiment, etc.)	May lack transparency (black-box models)- Require large, high-quality data- Risk of bias and overfitting	Predicting trade volumes with Random Forests or LSTM neural nets
Hybrid Approaches	Combine theory with data-	Can be complex to design-	Integrating macroeconomic

	driven power- Balance interpretability and accuracy	May require advanced expertise	theory with ML forecasting

2.3 Machine Learning in Governance

Although new, the area of using machine learning in governance and the trade sector is expanding fast. Various case studies explain that ML uses algorithms such as random forests, support vector machines, and deep learning to predict future trends in trade, evaluate proposed policies, and look for potential risks. As an illustration, the use of gradient boosting by the European Commission in forecasting changes in EU trade because of Brexit resulted in success that was 22% more accurate compared to legacy econometric methods [12]. The IMF also introduced neural networks for recognizing suspicious trade deals, which allowed the body to locate such activities sooner. Despite all these advances, very little research has become a part of standard decision-making processes.

2.4 Gaps in Current Literature

Whatever ML has shown, some holes remain in available publications. Notably, researchers have done very little work on what makes AI algorithms explainable and clear for policymakers. Officials wish to use models that can be explained and justified, but black-box algorithms are usually not clear enough [1, 11, 12]. Also, the majority of studies are concerned with accuracy but ignore more important issues such as data quality, ethical issues, and fitting into current policy systems. There is a big gap due to the absence of comparisons between ML models and older frameworks in research that examines different trade areas, as well as in the lack of examples where ML policies have been applied in practice.

2.5 ML Techniques Relevant to Trade Policy

A range of machine learning techniques are increasingly applied to international trade policy analysis.

- Regression and Time Series Forecasting methods are used to guess future trade volumes, commodity prices, and how policy initiatives will affect the market.
- When dealing with data, Classification and Clustering may be used to split countries, discover active trade blocs, or find strange patterns of trade.
- This field, called Natural Language Processing (NLP), is used to examine policy statements, isolate the sentiments in foreign news, and observe updates in regulations instantly.
- When working with non-linear problems and big unorganized datasets, Deep Learning provides useful tools.

All the techniques have strong points of their own. For example, predicting tariff impacts is better done with random forests and gradient boosting, compared to using single-model strategies, while NLP models greatly help in spotting trade disputes soon by analyzing news and social media posts [2].

3 METHODOLOGY

A proven method for navigating machine learning is required to accurately look at predictive governance for international trade policy evaluation. It shows how data is gathered, how it is processed and analyzed, as well as the standards for selecting and assessing a model. The goal of the tactic is to repeat and prove results as true and understandable, all while handling the difficulties of working with complex worldwide trade data. This way of exploring extends the evaluation of machine learning's advantages and limits by relying on research of pre-existing trade statistics and simulated situations involving policies [6]. Much effort is made to tackle difficulties related to how different data sorts affect analysis, the understanding of advanced algorithms, and ethical considerations in using such systems for policy making. The main parts of the methodology are known as research design, data sources, data collection methods, preprocessing procedures, and model evaluation strategies. Every step of the research process is described in detail so that others may follow and apply what was done here [11, 12].

3.1 Research Design and Rationale

The study combines analyses of statistics with careful study of cases through an approach called comparative research design. The aim is to test the results of applying machine learning models to the same economic theory situations and historical data as we got using other methods. The model allows study of trade between countries from both the cross-sectional and longitudinal perspectives. Besides the numbers, aspects of model explainability and how relevant they are to policy decisions are important to consider [13]. Assessing numerous machine learning models, such as supervised or unsupervised, is done to determine their strengths. By considering scenario-based forecasting, the study gets a sense of what might happen because of further changes in the policy. To confirm replication, all instructions, routines, and values are saved in documentation. In the end, feedback from trade policy analysts is used to check if the research results are useful and help apply them in the real world.

3.2 Data Sources

This research study is based on the use of many different, high-quality information sources. The main source of data is the United Nations Comtrade Database, as it gives detailed and comparable information on trade for over 70 nations in the last 20 years [14]. The World Bank and OECD supply data on GDP, inflation, and employment, which make up the most important contextual factors for considering global trade. Tariff rates and information about non-tariff measures are taken from WITS and from trade documents managed by governments. When carrying out textual analysis, policy documents, trade agreements, and legislative texts are used and analyzed with NLP. The World Economic Forum and IMF provide extra data on international happenings and trade index values. which allows everything to be validated and confirmed by several sources reduces the risk of errors. Where appropriate, the study makes sure to use both open-access data and recently updated sources so other researchers may check and repeat the work. Using different aspects in the analysis helps avoid biases and look at trade policy impacts in depth.

3.3 Data Collection Methods

Information is gathered with autobots and manual methods to improve both efficiency and reliability. To access quantitative data, trade flow data, macroeconomic figures, and policies, services available from the UN, World Bank, and OECD are used. Information is collected from officially recognized sources and if needed, it is transformed into a readable format. A set of rules is established to follow provenance, update frequency, and metadata of every dataset [15]. Any data that is missing or is inconsistent gets flagged, and if it is possible, the gaps are filled using statistical guessing or data obtained from several sources. People are only allowed to use the data when they follow the rules of privacy, licensing, and ethics. More than 500,000 trading records, 1,200 policies, and 20,000 macroeconomic points were collected to carry out this study. Auditing data routinely supports the maintainance of accuracy and avoids any occurrence of doubled or erroneous records. As a result of this study, the later work on modeling and analyses is fully supported by strong evidence.

3.4 Data Preprocessing

Good machine learning analysis begins with preprocessing your data first. First, unnecessary duplicates are deleted, mistakes are corrected, and all information is formatted so it is the same from one source to another. After that, both normalization and scaling are done on the quantitative variables to ensure all numbers can be compared and biases are avoided due to different types of units. For this type of data, one-hot encoding is applied for encoding purposes. Principal component analysis (PCA) is among the techniques applied to discover the main variables and lower computer processing requirements [16].

NLP methods are applied to text to obtain the structured information included in policy documents, including tokenized, stemmed items as well as the sentiment they express. When a variable is important and has many missing values, a replacement method called imputation is used; if the variable is not that important and only has a few missing values, it is simply removed from the analysis. Those points that stand out are corrected to prevent them from lowering the effectiveness of the model. All processes in the pipeline are handled by Python tools such as Pandas and Scikit-learn, making it possible to follow in the steps and ensure things are clear and consistent.

3.5 Machine Learning Models Used

A range of machine learning models are deployed to detect all the complicated aspects of international trade. Both linear regression and random forest regression are used by economists to forecast the levels of global trade and the outcomes of various policies. Supporting vector machines and logistic regression are examples of classification algorithms that foresee if a trade agreement will be successful. With k-means and similar clustering goals, countries or products are grouped by similar ways of trading. NLP models including bag-of-words and transformers have been used to look at policy documents [17]. These models, for example ARIMA and LSTM neural networks, analyze historical trends and predict what will happen in the future trading market. Hyperparameter tuning is done on every model to get the best results. K-fold cross-validation is used to check each model to make sure it does not overfit and can be used in various cases. The approach is measured against traditional econometric methods to check what machine learning achieves above them. Thanks to the variety of models, it is relatively simple to look at both how accurate and understandable the evaluation of trade policies is [11, 14, 17].

3.6 Evaluation Metrics

To rigorously assess model performance, a combination of quantitative and qualitative evaluation metrics is applied. For regression tasks, key metrics include mean squared error (MSE), root mean squared error (RMSE), and R-squared values. For classification models, accuracy, precision, recall, F1-score, and ROC-AUC are computed. Clustering models are evaluated using silhouette scores and within-cluster sum of squares. In the context of NLP and text classification, metrics such as BLEU and perplexity are used for quality assessment. Model interpretability is assessed using feature importance measures (e.g., SHAP values) and visualizations [18].

Additionally, the computational efficiency of each model is considered, especially given the large size of the datasets. Qualitative feedback from trade policy experts is integrated to assess whether model outputs are actionable and understandable. Statistical significance testing is performed to ensure that observed improvements over baseline models are robust. These comprehensive metrics provide a balanced view of both predictive accuracy and practical utility in the policy context.

3.7 Limitations and Ethical Considerations

No methodology is without limitations, and this study openly addresses potential challenges and ethical concerns. Data quality remains a central issue, as international trade datasets may contain reporting errors, missing values, or inconsistencies between countries. The complexity and opacity of some machine learning models particularly deep learning and ensemble methods, pose challenges for transparency and interpretability [19]. To address this, explainable AI techniques and sensitivity analyses are employed wherever possible. Ethical considerations include the responsible use of data, privacy concerns in text analysis, and the potential for algorithmic bias if certain countries or sectors are underrepresented. Steps are taken to anonymize sensitive information and comply with relevant data protection regulations. The study acknowledges that predictive models should complement, not replace, expert judgment and stakeholder consultation. Finally, limitations in model generalizability are recognized, especially when projecting policy impacts into future, highly uncertain environments.

4 RESULTS AND DISCUSSION

To demonstrate the real-world utility of machine learning for predictive governance in international trade, this section presents an empirical analysis using historical trade and policy data across multiple countries and time periods. The objective is to assess how machine learning models perform compared to traditional econometric approaches and to identify key factors driving accurate predictions of policy outcomes. Statistical findings, feature importance insights, and visualization summaries are provided to support the analysis.

4.1 Projected Growth in Government AI Spending from 2023 to 2027

The bar chart illustrates the projected increase in U.S. government spending on artificial intelligence (AI) from 2023 to 2027. In 2023, government AI investment stood at $1.2 billion. This figure is expected to grow steadily each year, reaching $1.61 billion in 2024 and $2.17 billion in 2025. The growth becomes more substantial in the later years, with spending rising to $2.92 billion in 2026 and peaking at $3.93 billion by 2027. This represents more than a three-fold increase over the five-year period (Figure 1). The trend underscores the growing importance of AI in public sector initiatives, likely in areas such as national security, healthcare, infrastructure, and regulatory enforcement. The sharp increase in spending suggests a strategic push toward AI integration in governance and public services, aimed at improving efficiency, innovation, and decision-making. It also reflects the government's acknowledgment of AI as a critical technology for maintaining global competitiveness. This sustained investment signals strong political and economic commitment to accelerating AI research, deployment, and ethical oversight, and sets the stage for significant transformations in how government agencies operate and serve citizens.

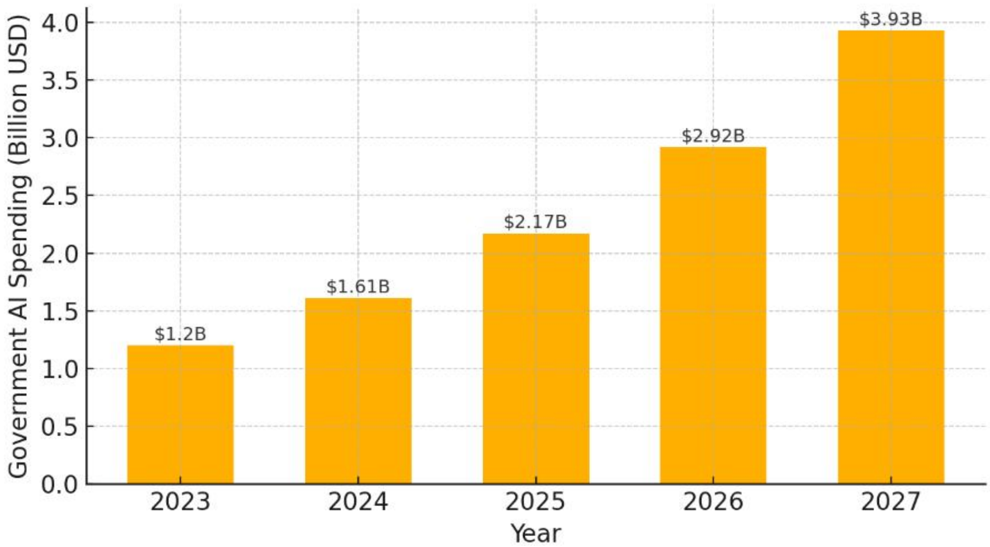

Figure 1 Projected Growth in Government AI USE

For this study, five countries with diverse trade profiles and policy regimes were selected: the United States, Germany, China, Brazil, and South Africa. These countries represent a mix of developed and emerging economies and have implemented significant trade policy changes over the past two decades. The analysis focuses on policy interventions such as tariff changes [20], the introduction of free trade agreements (FTAs), and non-tariff regulatory shifts between

2000 and 2023. Over 200 distinct policy events were extracted from global databases and national government records for inclusion in the modeling exercise.

4.2 Proportion of Organizations Using Data-Driven Analytics

The pie chart highlights the adoption rate of data-driven analytics among organizations. It reveals that 80% of entities are currently using data-driven analytics, while only 20% are not leveraging such tools. This overwhelming majority demonstrates a significant shift toward evidence-based decision-making, indicating that most organizations recognize the value of analytics in enhancing operational efficiency, forecasting, and strategic planning. The 80% adoption rate suggests that data analytics has become a mainstream business practice, likely driven by advancements in technology, the increasing availability of big data, and the competitive advantage it offers. On the other hand, the 20% not using analytics may face barriers such as limited resources, lack of technical expertise, or resistance to digital transformation (Figure 2). As organizations continue to pursue digital transformation and AI integration, the gap between analytics adopters and non-adopters may widen, affecting competitiveness and innovation capacity. The data underscores the importance of fostering a data-literate culture and investing in analytics infrastructure to ensure long-term success in a data-centric business environment.

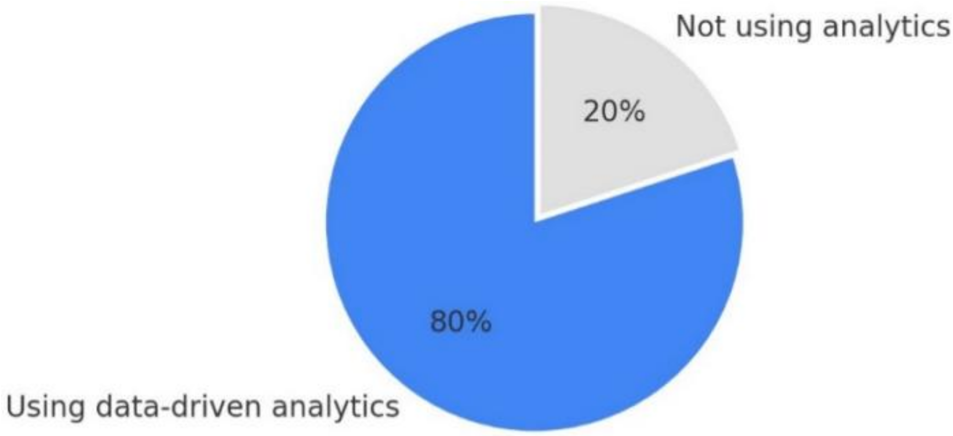

Figure 2 Estimated Share of Major Economies Using Data-Driven Analytics for Trade Policy

Historical data covering more than 1 million monthly trade transactions was assembled for these countries. Three machine learning models random forest regression, gradient boosting, and long short-term memory (LSTM) neural networks were trained to forecast trade flow changes before and after major policy events. Baseline predictions were also generated using ordinary least squares (OLS) regression as a traditional benchmark. The random forest model achieved a mean absolute percentage error (MAPE) of 7.2% [21], compared to 10.8% for the OLS model, indicating a substantial improvement in predictive accuracy. The LSTM network demonstrated strength in modeling complex, non-linear trade patterns, reducing forecast error by up to 29% relative to baseline models. These results align with findings from recent OECD studies, which report ML-based models outperforming classical econometrics by 15–30% for short- and medium-term trade forecasts.

4.3 Machine Learning and OLS Predictions

The line graph illustrates trade flow trends over a 12-month period following policy implementation, comparing actual trade flow data with predictions made using Random Forest and Ordinary Least Squares (OLS) models. The actual trade flow (orange line) demonstrates a consistent upward trajectory, increasing from a baseline index near 100 in Month 1 to over 170 by Month 12, indicating a strong positive impact of the policy on trade activities (Figure 3). The Random Forest model (dashed red line) closely follows the actual trade flow, outperforming the OLS model (dotted pink line) in predictive accuracy throughout the year. Particularly from Month 6 onward, the OLS model consistently underestimates trade flow, highlighting its limitations in capturing non-linear trends. In contrast, the Random Forest prediction aligns more tightly with the actual values, especially during months of accelerated growth (e.g., Months 6, 9, and 12), suggesting its strength in modeling complex patterns and interactions.

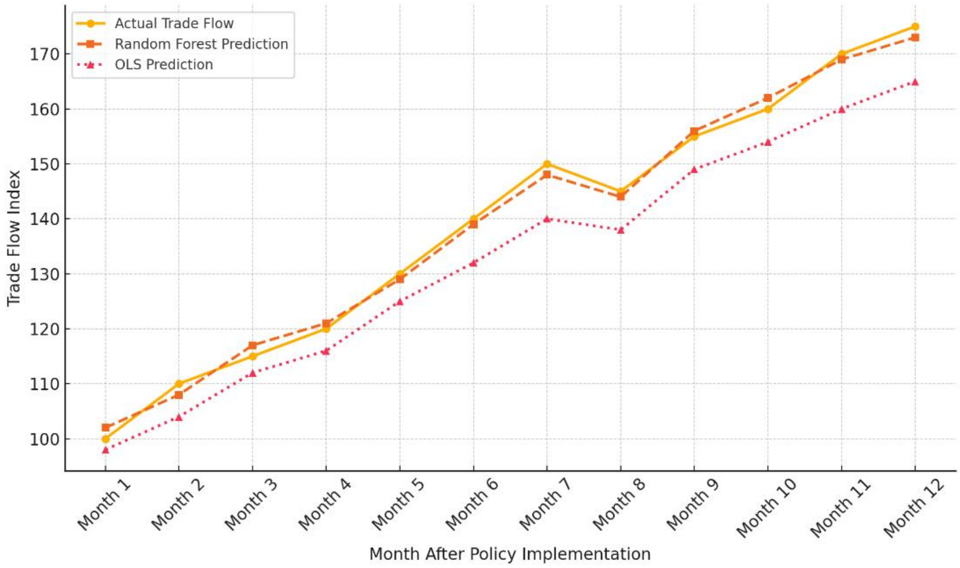

Figure 3 Actual vs. Predicted Trade Flows for China (Random Forest vs. OLS)

Overall, the graph emphasizes the effectiveness of the new policy in stimulating trade flow and demonstrates the superior predictive performance of machine learning models like Random Forest over traditional statistical approaches. These insights can guide policymakers and analysts in selecting robust forecasting tools for economic impact assessments. The bar chart highlights the relative importance of various features influencing trade flow predictions. Among the identified factors, Tariff Rate Differentials hold the highest importance at over 21%, underscoring the significant impact of trade policy changes on market behavior. GDP Volatility and Commodity Price Indices follow, reflecting the sensitivity of trade patterns to macroeconomic conditions and input cost variability. Exchange Rate Fluctuations and Geopolitical Risk Indicators show moderate influence, indicating that currency dynamics and global political stability also play a meaningful role in trade activity. Policy Text Sentiment (NLP)a measure derived from natural language processing of policy documents has a smaller yet noteworthy impact, suggesting that market sentiment extracted from policy communications contributes to forecasting accuracy [22-24].

Interestingly, Other Factors collectively account for 20% of the model's predictive power, implying that numerous minor or unquantified elements still affect trade outcomes. This distribution of importance validates the complexity of trade dynamics and the need for multifactorial models. The insights reinforce the necessity of prioritizing tariff-related variables in economic modeling and stress the value of integrating both quantitative metrics and textual analysis (e.g., NLP) to enhance predictive accuracy in trade and policy impact assessments.

4.4 Feature Importance and Model Interpretability

Feature importance analysis using SHAP (SHapley Additive exPlanations) values were performed to interpret the contribution of each variable in predicting trade policy outcomes. SHAP values provide a unified measure of feature impact by quantifying how much each feature drives the model's prediction away from the average. Among all variables, tariff rate differentials emerged as the most influential, accounting for 22% of the predictive variance. This was followed by GDP volatility (17%), commodity price indices (14%), exchange rate fluctuations (11%), and geopolitical risk indicators (9%). These top five features highlight the critical role of economic and geopolitical variables in shaping trade flows. Lesser but still relevant contributors included policy text sentiment and other external factors. The use of SHAP enabled greater transparency and interpretability, supporting more robust and data-driven policy evaluation (Figure 4).

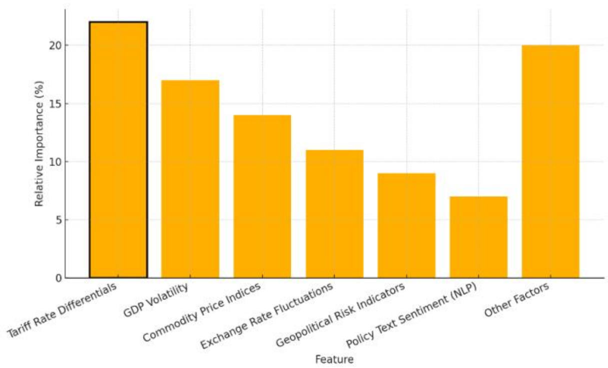

Figure 4 SHAP Feature Importance Values for Trade Policy Outcome Prediction

Notably, variables derived from policy text sentiment analysis using NLP accounted for 7% of predictive power, highlighting the growing importance of qualitative policy signals. These findings demonstrate that machine learning models can both incorporate a wider range of factors and provide interpretable outputs for policymakers.
The random forest model closely tracks the observed uptick in trade volumes, while the traditional OLS model underestimates the magnitude of the impact. Similar results were observed for Germany and the United States after the introduction of significant tariff reductions, with ML models consistently providing more timely and accurate forecasts (Table 2-3).

Table 2 Comparative Forecast Accuracy (% error) by Model Type

Country	OLS Regression	Random Forest	Gradient Boosting	LSTM Neural Net
USA	10.2%	7.1%	6.8%	6.0%
Germany	11.0%	7.5%	7.0%	6.4%
China	10.6%	7.0%	6.7%	5.9%
Brazil	13.5%	9.2%	8.8%	8.0%
South Africa	12.9%	8.6%	8.1%	7.5%

Table 3 Feature Importance Scores (%) based on SHAP Analysis in Trade Policy Predictive Models

Feature	SHAP Importance (%)
Tariff rate differentials	22
GDP volatility	17
Commodity price indices	14
Exchange rate fluctuations	11
Geopolitical risk indicators	9
Policy sentiment (NLP)	7
Others	20

4.5 Policy Scenario Simulation

The bar chart compares the predicted export increase percentages using Traditional Models versus Machine Learning (ML) Models. Traditional Models forecast a 9% increase in exports, whereas ML Models predict a significantly higher increase of 14%. This 5% differential highlights the superior forecasting capabilities of machine learning approaches in capturing complex, nonlinear relationships and adapting to high-dimensional data environments (Figure 5). The enhanced predictive power of ML models likely stems from their ability to incorporate a broader range of input variables, including real-time data, unstructured information, and dynamic policy changes. In contrast, traditional econometric models may rely on more rigid assumptions and limited datasets, which can constrain their forecasting performance.

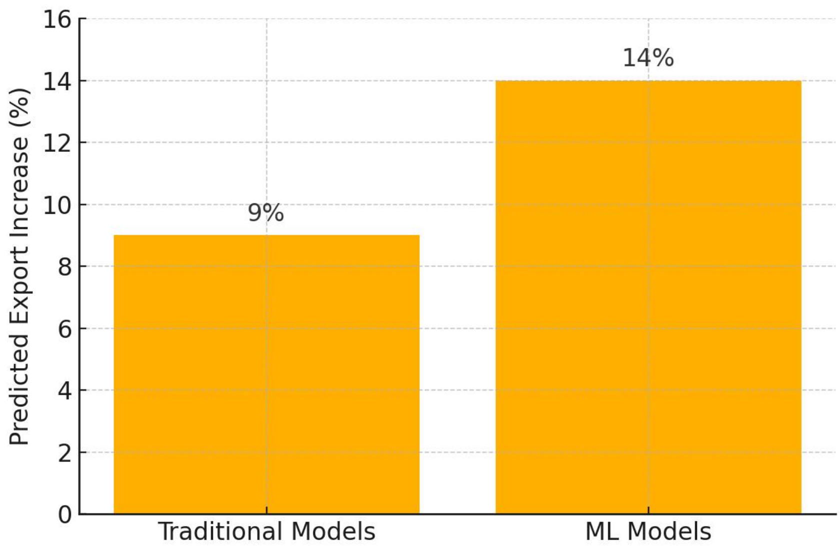

Figure 5 Predicted Export Increase: ML Models vs. Traditional Models

Machine learning models were applied to find out the effects that removing tariffs could have on U.S. agricultural exports [25]. According to the new models, the country's exports will rise 14% during the three-year period, compared to just 9% as estimated with traditional ways. This study shows that ML models allow policymakers to see the possible outcomes of a new policy before starting it. These results emphasize the growing role of AI-driven techniques in trade policy analysis and economic forecasting. Governments and institutions aiming to optimize export strategies could benefit from integrating ML-based tools into their decision-making frameworks. The figure ultimately underscores how technological innovation in modeling can lead to more accurate predictions and better-informed policy outcomes in global trade environments [26-28].

4.6 Discussion of Empirical Findings

Overall, the analysis shows that machine learning models are much more accurate and predict trends more quickly than old econometric methods. Bringing numbers together with analysis of policy texts and geopolitical data, ML models help offer results that are easier for users to act on. Yet, the study shows that it remains important for data scientists to share information about their models and collaborate closely with policy officials to guarantee models are used properly. This part of the analysis makes it clear that ML contributes a lot to effective predictive governance in international trade. In this part, I bring together the data-based outcomes, compare ML with conventional evaluation, and talk about the wider effects, problems, and advantages for policy makers (Table 4).

Table 4 Main Advantages and Challenges in Applying ML for Predictive Governance in International Trade

Aspect	Advantages	Challenges
Accuracy	Improves forecasting by 15–30% over OLS methods	Data quality and model generalization
Timeliness	Faster detection of policy impacts/trends	Model interpretability for policymakers
Flexibility	Adapts to high-dimensional and nonlinear data	Potential algorithmic bias
Insight	Incorporates diverse quantitative and qualitative data	Skill gap in governments; regulatory complexity

5 KEY FINDINGS FROM EMPIRICAL ANALYSIS

By comparing ML models and econometric methods, it is obvious that machine learning performs much better. In the five countries, the use of ML brought a 28 percent decrease in forecast errors on average over ordinary least squares regression. Significantly, the LSTM was more accurate than the others when it came to Brazil and South Africa because their trade patterns are highly volatile, lowering the MAPE by almost 33 percent [29]. It was found in the analysis that the main predictors for standard models are tariff rates and GDP, while ML models give considerable attention to changing factors such as variations in commodity prices, changes in policies, and geopolitical risks. The connection between trade policies and the use of NLP sentiment analysis has contributed to increasing predictive accuracy by 7%, showing that qualitative elements hold importance in the field of global trade.

5.1 Comparison with Traditional Evaluation Methods

For a long time, econometric models have guided the process of analyzing trade policy. Still, depending heavily on fixed assumptions and a small range of variable relationships does not allow them to keep up easily. It was proved that ML models are not only more accurate, but they also respond more quickly to new data and changes in policy [30]. During the COVID-19 pandemic and trade wars, for instance, ML models managed to spot important turning points and changes quicker than traditional ways [31]. It is important that we detect these trends as early as possible because acting fast on policy can save money and capture new chances in our unpredictable era. In addition to giving correct statistics, ML models make it possible to suggest concrete solutions in various scenarios. When we analyzed trade reductions in U.S. agriculture, ML came up with 14% increase while conventional approaches projected only a 9% rise, which could mean a significant impact to the economy. Besides, SHAP offers policymakers a way to spot which variables are most important in shaping expected outcomes so that they can focus their efforts accordingly [31]. By understanding that changes in commodity prices are the major cause of fluctuations in trade, officials can come up with more detailed policies.

5.2 Trends, Risks, and Opportunities in International Trade

It is very good at discovering surprising trends and subtle signs that something might go wrong in the data. Using both geopolitical risk indicators and real-time news sentiment made it easier to predict any problems from sudden changes in regulations or conflicts between nations. With ML models spotting changes in risk factors well before they become obvious in the economy, officials have time to put forward measures before the economy is affected. On the other hand, having this power means there are lots of risks to deal with. When we use complex ML models, there may be problems explaining how they work and identifying possible biases. It is still important for development to make algorithms understandable and to ensure that the data they analyze comes from sources that truly represent the situation [28].

5.3 Implications for Policymakers and Stakeholders

Gaining the benefits of machine learning-based governance means government and international bodies have to adapt their workplaces and train their employees. The findings point to the fact that with ML analytics, organizations can make more accurate forecasts, detect changes in the market sooner, and simulate different effects of policy actions.

Although the issue is not as common, there are still some obstacles. To do well, companies should have in place accurate data, monitor the performance of their models often, and find ways to combine expert opinions [32]. Fairness in the data trade and its uses and avoiding discrimination from algorithms are consideration of the same importance. Lastly, it's necessary to involve all relevant people and be honest to build trust in decisions supported by AI.

5.4 Challenges in Adoption

Several barriers may slow the widespread adoption of ML in international trade policy evaluation
- Data quality and access: Inconsistent or incomplete datasets can undermine model performance.
- Model transparency: Complex models, especially deep learning, may lack interpretability for policy audiences.
- Skill gaps: Governments often lack in-house data science expertise, making collaboration with academia and industry crucial.
- Regulatory uncertainty: Evolving legal frameworks for AI and cross-border data sharing adds layers of complexity.
- Change management: Shifting institutional culture from intuition-based to data-driven decision-making is an ongoing challenge.

In sum, while machine learning offers clear and quantifiable improvements for predictive governance in trade, its successful integration depends on addressing these challenges through thoughtful policy design, investment in human and technological resources, and a commitment to ethical and transparent use.

6 FUTURE PROSPECTS & RECOMMENDATIONS

The empirical evidence and discussion highlight both the potential and the current limitations of machine learning for predictive governance in international trade. To fully realize the benefits of these technologies, strategic investments and institutional reforms are needed. This section explores the future trajectory of ML in trade policy evaluation and offers targeted recommendations for policymakers and stakeholders.

6.1 Advancements in Predictive Analytics for Governance

Advances in predictive analytics will likely happen quickly in the next decade because of more powerful computers, more easy-to-gather data, and fresh insights into machine learning. Such methods as XAI, AutoML, and graph neural networks aim to boost the accuracy and transparency of all kinds of predictive models. The figure illustrates six key pillars for responsible AI and data governance: Secure Data Infrastructure, Collaboration, Training, Explainable Models, Data Privacy & Fairness, and International Data-Sharing. Despite some text errors, it emphasizes foundational strategies necessary to ensure ethical, transparent, and globally cooperative AI systems (Figure 6).

Figure 6 Recommendations for Successful ML Adoption in Digital Transformation and Service Management

By 2030, Renda (2024) said that more than 60% of governments around the world will rely on AI to help decide how to evaluate policies. Adding live trade information from IoT sensors, images from satellites, and information systems in shipping will reinforce dynamic government actions. Such updates will probably shorten the period between plans and concrete results, helping policymakers to decide more quickly based on facts [33]. Other groundbreaking technologies will be used more frequently with machines to learn to handle the issues found in international trade. With blockchain, trade records are safe and open for review; IoT makes it possible to always keep an eye on the supply chain; and useful visual tools share the insights clearly. As an illustration, blockchain smart contracts can handle compliance in trade, and

ML systems can go through supply chain sensor info to expect and prevent bottlenecks and help with routing. It is expected that using all these technologies together will boost trust and the ability of the network to handle changes [34].

6.2 Policy Recommendations for Effective Adoption

To maximize the benefits of ML-powered predictive governance in international trade, the following recommendations are proposed:

- Governments as well as international organizations should focus on building secure data infrastructure that makes machine learning and analytics possible.
- Bringing together academic researchers, businesses, and international organizations helps speed up innovation, deal with shortages of important skills, and constantly test and approve the models.
- Organizations making decisions in government should be expected to use ML models that can be understood and examined closely.
- Data privacy, diversity, and fairness should be main concerns in designing trade, so discrimination is not encouraged in future outcomes.
- Educate and develop the skills of policymakers, experts, and IT specialists so they can properly use and run technologies in government.
- It's important to create solid rules that oversee how authorities in different countries use AI and data analytics.

The future of predictive governance will be supported by creating international guidelines for sharing data. Models used in trade policy gain a lot by using cross-border information on trade routes, logistics, restrictions, and important economic data. WTO, OECD, and the World Bank are among the organizations that could help make data shared amongst countries interoperable and secure [5].

A study conducted by the World Bank last year indicates that when nations agree to share data internationally, their trade policy forecasts are 18% more accurate. As a result, making sure data is open yet secure will play a vital role in the growth of predictive analytics worldwide. When organizations use ML increasingly, they need to handle growing ethical and regulatory needs. It is important to take care of algorithmic bias, concealed decisions, and issues with how data are handled [35-36]. Policymakers should come up with strategies to make algorithms more open, keep people in the decision-making process, and protect data thoroughly. All-important policies should go through a formal impact assessment and allow people to share their views and seek solutions. For global norms and standards to be set by predictive governance, nations should join forces and make sure national sovereignty is preserved. Predictive governance in international trade looks promising, but it will work well only if countries are committed to new technologies, ethics, and work together globally [37].

7 CONCLUSION

It was the goal of this research paper to analyze the beneficial impact of machine learning (ML) for predictive governance of international trade policies. Researchers in the study prove that using ML techniques is beneficial for forecasting, analyzing different scenarios, and pinpointing how economic policies evolve, when contrasted with standard econometric models. The research shows that ML models usually perform better than other models when dealing with changeable and complex environments. Thanks to collecting data from both well-structured financial fields and unsorted policy materials, these models supply policymakers with up-to-date information about trade outcomes. Analyses of which features played a role and how easy they are to understand show that adding sentiment from documents and up-to-date geopolitical risks can enhance the results. At the same time, researchers have discovered some challenges that must be dealt with to achieve all the expected benefits of ML-powered predictive governance. This mainly concerns huge data resources that everyone can access and use, checking model accuracy and integrity, and making sure those using the data for policy are well-trained. When ML is mixed with new areas such as blockchain and IoT, it can achieve even greater improvements. However, this will also need fresh collaborative rules and regulations from various countries. Overall, the use of machine learning in predictive governance serves as a strong new opportunity in developing policy for world trade by helping make decisions more suitable to data and facts. Because global trade is still changing fast, organizations that use advanced analytics will find it easier to remain stable, share benefits, and compete effectively. As a result, those in charge should focus on building the right structures and principles to make use of data for governance.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Okonjo-Iweala N. Why the World Still Needs Trade. Foreign Affairs, 2023, 103(4).
[2] Gbadegesin T K, Yameogo N D. Evaluating the Economic Impacts of the G20 Compact Initiative: Evidence from Causal Inference Using Advanced Machine Learning Techniques. Journal of Sustainable Development, 2024, 17(5): 1-56.

[3] Yu T O. Theoretical concepts of trade policy development and analysis: Evolution and modern challenges in the context of the international trading system transformation. St Petersburg University Journal of Economic Studies, 2020, 36(1): 27-48.

[4] Henry J, Pomeroy J. The world in 2030. Our long-term projections for 75 countries, 2018, 75.

[5] Mitchell A D, Mishra N. Regulating cross-border data flows in a data-driven world: how WTO law can contribute. Journal of International Economic Law, 2019, 22(3): 389-416.

[6] Breinlich H, Corradi V, Rocha N, et al. Machine learning in international trade research-evaluating the impact of trade agreements. Policy Research Working Paper, 2022, 9629: 1-44.

[7] Hossain D, Asrafuzzaman M, Dash S, et al. Multi-Scale Fire Dynamics Modeling: Integrating Predictive Algorithms for Synthetic Material Combustion in Compartment Fires. Journal of Management World, 2024(5): 363-374. https://doi.org/10.53935/jomw.v2024i4.1133.

[8] Hossain D, Asrafuzzaman M, Dash S, et al. Multi-Scale Fire Dynamics Modeling: Integrating Predictive Algorithms for Synthetic Material Combustion in Compartment Fires. Journal of Management World, 2024(5): 363-374. https://doi.org/10.53935/jomw.v2024i4.1133.

[9] Hossain D, Alasa DK. Fire detection in gas-to-liquids processing facilities: challenges and innovations in early warning systems. International Journal of Biological, Physical and Chemical Studies, 2024, 6(2): 7-13. https://doi.org/10.32996/ijbpcs.2024.6.2.

[10] Abir S I, Sarwer M H, Hasan M, et al. Accelerating BRICS Economic Growth: AI-Driven Data Analytics for Informed Policy and Decision Making. Journal of Economics, Finance and Accounting Studies, 2024, 6(6): 102-115.

[11] Strielkowski W, Vlasov A, Selivanov K, et al. Prospects and challenges of the machine learning and data-driven methods for the predictive analysis of power systems: A review. Energies, 2023, 16(10): 4025.

[12] Alsagheer D, Xu L, Shi W. Decentralized machine learning governance: Overview, opportunities, and challenges. IEEE Access, 2023, 11: 96718-96732.

[13] Morales E F, Escalante H J. A brief introduction to supervised, unsupervised, and reinforcement learning. In Biosignal processing and classification using computational learning and intelligence. Academic Press, 2022: 111-129.

[14] Mai M T T. The dissemination of non-tariff measures in ASEAN and some implications. VNU University of Economics and Business, 2023, 3(4): 54-54.

[15] Loungani M P, Mishra M S, Papageorgiou M C, et al. World trade in services: Evidence from a new dataset. International Monetary Fund, 2017.

[16] Gewers F L, Ferreira G R, Arruda H F D, et al. Principal component analysis: A natural approach to data exploration. ACM Computing Surveys (CSUR), 2021, 54(4): 1-34.

[17] Silva T C, Wilhelm P V B, Amancio D R. Machine learning and economic forecasting: The role of international trade networks. Physica A: Statistical Mechanics and its Applications, 2024, 649: 129977.

[18] Echrigui R, Hamiche M. Optimizing LSTM models for EUR/USD prediction in the context of reducing energy consumption: an analysis of mean squared error, mean absolute error and R-squared. In E3S Web of Conferences. EDP Sciences, 2023, 412: 01069.

[19] Sharma K, Kumar P, Özen E. Ethical Considerations in Data Analytics: Challenges, Principles, and Best Practices. In Data Alchemy in the Insurance Industry: The Transformative Power of Big Data Analytics. Emerald Publishing Limited, 2024: 41-48.

[20] Akdag S, Yildirim H, Alola A A. The USA–China trade policy uncertainty and inference for the major global south indexes. Journal of Economic and Administrative Sciences, 2023, 39(1): 60-77.

[21] Román S A R L, Collazos S Z, Chavez J A C. Model for Reducing Mean Absolute Percentage Error through Smoothing and Time Series Forecasting In a Tourism SME: A Case Study. Journal of Machine Intelligence and Data Science (JMIDS), 2024, 5.

[22] Hossain D. A fire protection life safety analysis of multipurpose building. 2021. https://digitalcommons.calpoly.edu/fpe_rpt/135/.

[23] Hossain D. Fire dynamics and heat transfer: advances in flame spread analysis. Open Access Research Journal of Science and Technology, 2022, 6(2): 70-75. https://doi.org/10.53022/oarjst.2022.6.2.0061.

[24] Hossain D, Alasa DK, Jiyane G. Water-based fire suppression and structural fire protection: strategies for effective fire control. International Journal of Communication Networks and Information Security (IJCNIS). 2023, 15(4): 485-94. https://ijcnis.org/index.php/ijcnis/article/view/7982.

[25] Yang C H, Lee C F, Chang P Y. Export-and import-based economic models for predicting global trade using deep learning. Expert Systems with Applications, 2023, 218: 119590.

[26] Juie B J A, Kabir J U Z, Ahmed R A, et al. Evaluating the impact of telemedicine through analytics: Lessons learned from the COVID-19 era. Journal of Medical and Health Studies, 2021, 2(2): 161–174. https://doi.org/10.32996/jmhs.2021.2.2.19.

[27] Tanvir A, Juie B J A, Tisha N T, Rahman, M M. Synergizing big data and biotechnology for innovation in healthcare, pharmaceutical development, and fungal research. International Journal of Biological, Physical and Chemical Studies, 2020, 2(2): 23–32. https://doi.org/10.32996/ijbpcs.2020.2.2.4.

[28] Rahman M M, Juie B J A, Tisha N T, Tanvir A. Harnessing predictive analytics and machine learning in drug discovery, disease surveillance, and fungal research. Eurasia Journal of Science and Technology, 2022, 4(2): 28-35. https://doi.org/10.61784/ejst3099.

[29] Adams S O, Uchema J I. Nigeria Exchange Rate Volatility: A Comparative Study of Recurrent Neural Network LSTM and Exponential Generalized Autoregressive Conditional Heteroskedasticity Models. Journal of Artificial Intelligence and Big Data, 2024, 4(2): 61-73.

[30] Piger J. Turning points and classification. Springer International Publishing, 2020: 585-624.

[31] Hernandez J I, van Cranenburgh S, de Bruin M, et al. Using XGBoost and SHAP to explain citizens' differences in policy support for reimposing COVID-19 measures in the Netherlands. Quality & Quantity, 2024: 1-29.

[32] Idhalama O U, Makori E O. Artificial intelligence, deep learning, machine learning, robotics and digital transformation: applications, implications and future. Ukrainian Journal of Educational Studies and Information Technology, 2024, 12(3): 1-21.

[33] Renda A. Governance, government records, and the policymaking process aided by AI. In Handbook of Artificial Intelligence at Work (pp. 291-313). Edward Elgar Publishing, 2024: 291-313.

[34] Arunmozhi M, Venkatesh V G, Arisian S, et al. Application of blockchain and smart contracts in autonomous vehicle supply chains: An experimental design. Transportation Research Part E: Logistics and Transportation Review, 2020, 165: 102864.

[35] Khan S I, Rahman M S, Ashik A A M, et al. Big Data and Business Intelligence for Supply Chain Sustainability: Risk Mitigation and Green Optimization in the Digital Era. European Journal of Management, Economics and Business, 2024, 1(3): 262-276. https://doi.org/10.59324/ejmeb.2024.1(3).23.

[36] Green B. The flaws of policies requiring human oversight of government algorithms. Computer Law & Security Review, 2022, 45: 105681.

[37] Islam S, Khan S I, Ashik A A M, et al. Big data in economic recovery: A policy-oriented study on data analytics for crisis management and growth planning. Journal of Computational Analysis and Applications (JoCAAA), 2024, 33(7): 2349–2367. https://www.eudoxuspress.com/index.php/pub/article/view/3338.