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| RESEARCH ARTICLE

Assessing Geopolitical Risks and Their Economic Impact on the USA Using Data Analytics

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| ABSTRACT

Understanding geopolitical risks is a paramount aspect of examining the stability and resilience of national economies, specifically in today's rapidly evolving global surroundings. Advanced analytics in the big data era open unparalleled avenues toward the quantification and comprehension of geopolitical risks on the performance of the economy of the United States. The prime objective of this study was to analyze the impact of geopolitical events on the U.S. economy, to identify key risk factors and their economic implications as well as propose strategies for mitigating adverse effects. Datasets used in this exploration were collected from different reliable sources to assess sources of geopolitical risk data and their economic impact on the U.S. First, data on geopolitical risk were collated from a combination of real-time news reports, government databases, and international organizations involved in monitoring geopolitical events. Key sources for this included GDELT news and sentiment data, official reports from U.S. government agencies such as the Department of State and the Department of Defense about foreign policy, conflict, and security, while major financial news outlets like Bloomberg and Reuters provided moment-by-moment coverage of events in the geopolitical sphere. We applied the Geo-Risk-Regressor model, a form of multimodal design to predict geopolitical threats arising from economic indicators, real-time news sentiment, and government reports on geopolitical events. The Geo-Risk-Regression Model is an integrated set of machine learning algorithms, from time-series and NLP to econometric regression, on structured and unstructured data comprising economic indicators, real-time news sentiment, and government reports on geopolitical events. A rigorous structured procedure was followed in implementing the Geo-Risk-Regressor to analyze the economic impact of geopolitical risks in the U.S. To assess and evaluate the performance of the algorithms, two key performance evaluation metrics were utilized MSE & R-squared. Among all the models, the best performance was that of XG-Boost; it had the lowest MSE and highest R^2. Thus, XG-Boost is the best model fitted for the prediction of GPRD_THREAT, probably because of its robust optimization and also its capability to capture a lot of complicated patterns in data. The geopolitical threat level perceived using the proposed models will enable business organizations in the USA to identify and manage risks that may affect the operations of the business organizations. Companies can, therefore, understand factors that contribute to risk and develop contingency plans, enabling them to take proactive measures to mitigate negative impacts from geopolitical events. Predictive models will help businesses in America estimate the potential risks to their supply chains and create strategies for mitigating any disruptions that might come through geopolitical events.

| KEYWORDS

Geopolitical risks, economic impact, data analytics, Geo-Risk-Regressor, U.S. economy, risk mitigation, predictive modeling, policy recommendations

| ARTICLE INFORMATION

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1. Introduction

Background

As per Ahmad et al. (2024), understanding geopolitical risks is a paramount aspect of examining the stability and resilience of national economies, specifically in today's rapidly evolving global surroundings. Over the last three decades, as the world has grown more interdependent on aspects such as trade, technology, and multinational investments, geopolitical tensions in one part of the world are having a more sweeping impact on other distant economies some instances, instantaneously. All of these risks are crucial to understand and mitigate for the United States as a leading player in today's global economic environment. Buiya et al.(2024), contend that From trade policy and international sanctions to military conflict and political instability, geopolitical risk touches or has the potential to touch many sectors of the United States economy: finance, manufacturing, energy, technology, and agriculture. In light of that, even the local events-a sudden policy turn by a major oil-exporting nation, social disturbances in a region containing strategic trade routes can send ripples to American markets, affecting everything from stock prices to consumer sentiment. With these risks now having increasingly pervasive and persistent economic impacts, influencing not just trade and capital flows but also the economic welfare of ordinary citizens, the need for an objective assessment and prediction of these risks can never be felt more urgently.

Shawon et al. (2024), posit that historically, America has confronted various forms of geopolitical issues that have impacted its economic trajectory, sometimes in profound ways. For example, during the Cold War era, geopolitical risk was driven by ideological rivalry with the Soviet Union, in which U.S. policies formed and often reformed a variety of alliances and trade relationships around the world. These alliances created economic prosperity, regional stability, and assured energy resources through sometimes expensive financial and diplomatic aid programs and strategic partnerships. Zeeshan et al.(2024), argue that over the past decades, new dynamics came into play: the rise of China as an economic force became a paradigm-shifting development in global power dynamics; the Middle East remained volatile while elemental to energy supplies; and transnational issues like cybersecurity and climate change brought new dimensions to traditional geopolitical concerns. Each of these geopolitical developments has required the U.S. to rethink its economic policies and adapt to changing global landscapes, making a strong risk assessment framework important for anticipating and mitigating prospective adverse outcomes.

Sumon et al. (2024) articulate that advanced analytics in the big data era open unparalleled avenues toward quantifying and comprehending geopolitical risks on the performance of the economy of the United States. Having huge amounts of data on trade flows, capital markets, currency exchange rates, and social sentiment, will help policymakers, economists, and analysts make judgments about risk in real-time much better, with more sound, data-driven decisions. Today's analytical tools can incorporate structured and unstructured data, analyze it at scale, and generate actionable insights that in themselves would be unimaginable just a decade ago. Dogan et al. (2023), upholds that AI and ML are also reshaping the face of the discipline by allowing analysts to model and predict scenarios that, until lately, have been too complex to consider. These technologies analyze historical patterns, understand correlations across multiple variables, and identify faint signals of impending crises. The machine learning model, for example, can be trained with historical data on trade and political events to apply derived insights to predict future disruptions to supply chains due to rising tensions in a particular region. Corporate leaders and policymakers may use that knowledge proactively.

Objectives of the Study

The present study aims to conduct an in-depth analysis of the effects that different geopolitical events-international conflicts, policy changes, trade tensions, and security threats on the U.S. economy. The study's first objective is to assess how these events impact core economic indicators like GDP, inflation, trade balances, stock market performance, and foreign direct investment, assisting in ascertaining the direct and indirect economic ramifications of geopolitical risks. The second objective revolves around pinpointing and understanding the important risk factors that will accompany these events, including supply chain disruption, volatility in energy prices, fluctuation of currency, and shifting investor confidence. It is through the identification of these factors that the study tries to outline implications on the economic prospects and determines which sectors and areas are more vulnerable. Furthermore, this research will seek to develop practical strategies that mitigate such adverse effects and, in so doing, provide proactive steps required by policymakers, businesses, and investors in devising a manner in which economic resilience and stability are increased against changes in geopolitical challenges.

II. Literature Review

Overview of Geopolitical Risks

Gong & Xu (2022), states that geopolitical risks revolve around the potential threats brought about by political instability, policy shifts, conflicts, or events on the international scene that may affect the prospects of various aspects of the global economy. Geopolitical risks generally are always varied, involving sets of events and conditions which could result in market volatility, retarded economic growth, or even crisis. Geopolitical risk, in general, may be categorized into a few types: conflicts, economic risks, political risks, and transnational issues. Conflicts involve war and terrorism, while economic risks include trade sanctions and protectionism. Caldara & Iacoviello, (2022), asserted that political risk involves a change in regime, corruption, or instability within a government. Transnational issues include cybersecurity threats, pandemics, and climate change. Each of these types differs in its implications for economic stability and market behavior as it affects trade, investment, and consumer confidence.

Over time, a variety of geopolitical events have shaped the U.S. economy in profound ways, illustrating that what happens globally can indeed impact the domestic marketplace. For example, the 1973 oil crisis-enacted by OPEC's decision to implement an oil embargo-resulted in skyrocketing energy prices to eventually plunge the U.S. into double-digit inflation and a deep recession. The volatility in oil prices due to the Gulf War in the early 1990s disrupted global trade routes and hence sent ripples of instability in U.S. markets. Other significant events include the 9/11 terrorist attacks of 2001, when besides actual losses in the U.S. (Li et al., 2024). Infrastructure and lives, the general economy suffered a serious blow with stock markets falling hedged and travel industries receiving discouraging jolts. More recently, the 2018 U.S.-China trade war illustrated how economic policies and diplomatic tensions between the two major global powers could create disruptions to supply chains but also have an ominous effect on stock markets and a shifting of trade balances. Each of these events Said, diverse ways that geopolitical risk can impact the American economy, how required an understanding of geopolitical risk is to manage the economic burden.

Economic Impact of Geopolitical Risks

Zeeshan et al. (2024), contend that geopolitical risk has direct and indirect economic consequences on sectors and economic indicators in general. Direct consequences involve immediate disruptions, such as physical damages emanating from conflicts or sanctions that restrict trade flows and investment to specific sectors. Examples include that, in cases of conflict, infrastructure is destroyed, businesses are forced to cease operations, and supply chains are disrupted in most cases. Indirect repercussions tend to persist longer and might at times be more obscurely valued. The indirect impacts can be a loss of market confidence, changes in consumer expenditure, and long-term shifting patterns of investment. For instance, when geopolitical events lead to uncertainty, companies may delay investments, households reduce spending, and markets may become volatile as investors pull out of high-risk sectors or regions.

Reivan et al (2023), argues that key variables that are affected by geopolitical events include the stock exchange, FDI, balance of trade, currency exchange rate, and interest rate conditions. Stock markets, especially in the United States, have been seen to be quite sensitive to geopolitical shocks; even perceived risk could result in sudden fluctuations in share prices. For instance, the S&P 500 would have usually trended lower with rising conflicts or political instability. Geopolitical risk also makes investors avoid FDI, with the latter seeking safer climes for their capital during periods of uncertainty. Trade is another very critical area where geopolitical events take their toll. For instance, sanctions disrupt trade routes and result in losses in exports or an increase in the cost of imports. Lastly, currency exchange rates and interest rates are often volatile in times of geopolitical tension, as investors may either flock to or abandon the U.S. dollar depending on the risk climate, which in turn influences the Federal Reserve's monetary policy decisions.

Data Analytics in Risk Assessment

According to Shahzad et al. (2022), data analytics plays a transformative role in the identification and prediction of geopolitical risks, enabling policymakers and businesses to better cope with these types of uncertainties. Traditionally, geopolitical analysis would be based on largely qualitative methods, historical context, and expert judgment. Big Data, Advanced Analytics, and Artificial Intelligence mean risk assessment is shifting toward fact-based insights which may prove more accurate, timely, and nuanced. Data analytics does this through the analysis of massive volumes of data from news articles, social media feeds, market data, and government reports for a deeper understanding of the underlying potential risks. For example, NLP can process large volumes of text-based information for pattern noticing and sentiment monitoring-almost an early warning system for geopolitical tension that ought not to be underestimated in real-time monitoring and risk management.

Various algorithms and techniques exist within data analytics to assess and predict geopolitical risks. Predictive models, for example, use historical data of geopolitical events and their consequences in the economic sphere to project the probable effects of similar events in the future. Regrettably, machine learning algorithms are of particular use in this respect, since they can uncover complex, non-linear patterns in data that might otherwise remain unseen using traditional analytical techniques. Time-series models, sentiment analysis, and econometric models usually come into play to analyze the trend and patterns of the market data, with a clearer view of what the implications of geopolitical risks could be on economic factors such as stock prices or inflation (Ahmad et al. 2024). Finally, scenario analysis and Monte Carlo simulations are also used quite frequently to consider different future scenarios, taking into consideration the probability of various outcomes, something meaningful for contingency planning. Pragmatically, such methodologies offer organizations a proactive way of dealing with risks. Using these, an organization can determine in practice when a threat may become real, its likelihood, and respond appropriately.

III. Methodology

Datasets used in this exploration were collected from different reliable sources to assess sources of geopolitical risk data and their economic impact on the U.S. First, data on geopolitical risk were collated from a combination of real-time news reports, government databases, and international organizations involved in monitoring geopolitical events. Key sources for this included GDELT news and sentiment data, official reports from U.S. government agencies such as the Department of State and the Department of Defense about foreign policy, conflict, and security, while major financial news outlets like Bloomberg and Reuters provided moment-by-moment coverage of events in the geopolitical sphere [Pro-AI-Robikul, 2024]. For economic indicators, information was culled from the U.S. The sources are the Bureau of Economic Analysis for GDP statistics, the Federal Reserve for interest rate and inflation data, and stock market indices such as S&P 500 and Dow Jones sourced from Yahoo Finance and the Federal Reserve Economic Data system. Trade volumes and balances were sourced from the U.S. Census Bureau and the International Monetary Fund for the correct correlation of economic responses to geopolitical events. This multi-source approach was to ensure comprehensive data gathering on time so that a sound analysis of how geopolitical risks impact the U.S. economy was achieved.

Model Utilized

We applied the Geo-Risk-Regressor model, a form of multimodal design to predict geopolitical threats arising from economic indicators, real-time news sentiment, and government reports on geopolitical events. The Geo-Risk-Regression Model is an integrated set of machine learning algorithms, from time-series and NLP to econometric regression, on structured and unstructured data comprising economic indicators, real-time news sentiment, and government reports on geopolitical events. The key features of the model included gauging the response of public and media sentiment to unfolding events, predictive modeling of shifts in the economy based on historically defined risk patterns, and anomaly detection to flag unusual market reactions that are indicative of further analysis.[Pro-AI-Robikul, 2024] Moreover, it is an adaptive model since it constantly recalibrates its predictions to new data, which is so important during the analysis of quickly changing geopolitical situations. Thus, the Geo-Risk-Regressor was selected for its robust handling of complex, high-dimensional data and its ability to produce timely insights, multidimensional data, and the capability to provide insights in a timely way. Therefore, it is quite good for finding the correlations between geopolitical events and their economic impact on such key indicators as GDP, trade volume, or stock prices in the U.S.

Data Preprocessing

Suitable code snippets were computed which provided detailed data preprocessing, where several important steps are carried out. First, the code removed three unimportant columns ('Unnamed: 9', 'Unnamed: 10', and 'event') by using df. drop(). Then it converts the object-type 'date' column to datetime format using pd.to_datetime(). Secondly, the code checked the missing values across all columns, showing zero for all eight remaining columns: DAY, N100, GPRD, GPRD_ACT, GPRD_THREAT, date, GPRD_MA30, GPRD_MA7. After row-dropping operations were likely unnecessary given there were no missing the final cleaned dataset contains 14,476 entries with 8 columns, all showing complete non-null counts. The data types were appropriately set with integers for DAY and N100 as int64, datetime64[ns] for the date column, and float64 for the GPRD-related metrics.

Model Implementation

A rigorous structured procedure was followed in implementing the Geo-Risk-Regressor to analyze the economic impact of geopolitical risks in the U.S.: first, advanced data preprocessing was deployed through cleaning, normalization, and organization, with special considerations on time series, news sentiment data, and other structured economic indicators like GDP and stock indices. Second, model training was started for the Geo-Risk-Regressor by training historical data on geopolitical events tagged with economic outcomes so that the model learns from the patterns and correlations. Thirdly, unsupervised learning was utilized in the training phase for anomaly detection, while for prediction tasks, we utilized supervised learning techniques[Pro-AI-Robikul, 2024]. To validate the performance of the model, the analyst split the dataset into training on 70% of the historical data and validating the remaining 30%. This operationalization provided insight into the predictive accuracy of the model. To assess and evaluate the performance of the algorithms, two key performance evaluation metrics were utilized MSE & R-squared. These metrics helped fine-tune the model to ensure Geo-Risk-Regressor provided reliable and actionable insights into how geopolitical risks affected the U.S. economy.

IV. Analysis

Exploratory Data Analysis

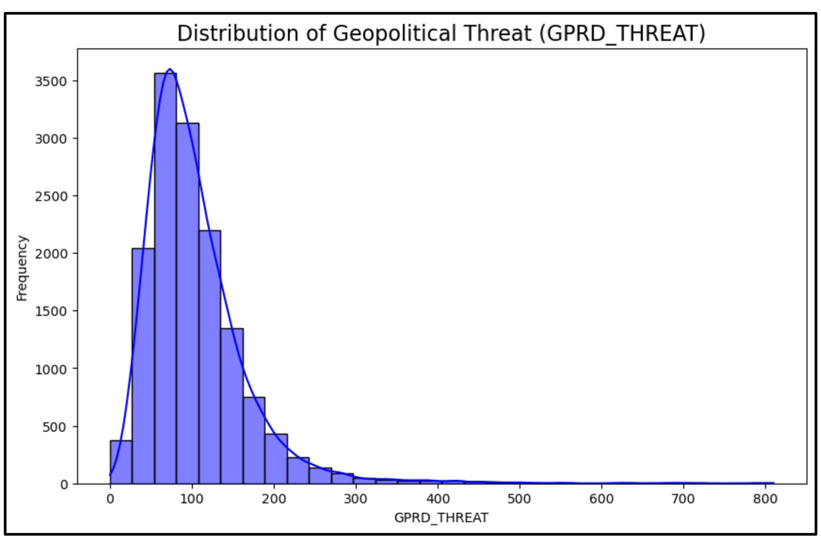

Figure 1: Portrays the Distribution of Geopolitical Threat

This histogram above displays the distribution of the Geopolitical Threat index, GPRD_THREAT. This distribution is highly right skewed, which would imply that lower magnitudes of threat are common, but higher values of geopolitical threats are infrequent. The peak or mode lies between approximately 80 and 100, suggesting that most of the data points lie in this range. The higher the level of threat, the lower the frequency, with a long tail out to higher values that would suggest extremely high geopolitical threats are far less common. Skewness in the distribution suggests that while geopolitical risks are predominantly moderate, extreme geopolitical threats are rare and may form significant outliers, to which one shall pay special attention when studying their economic consequences. The overall shape of this distribution is common in data sets when there are occasional extreme events that have relatively high impacts.

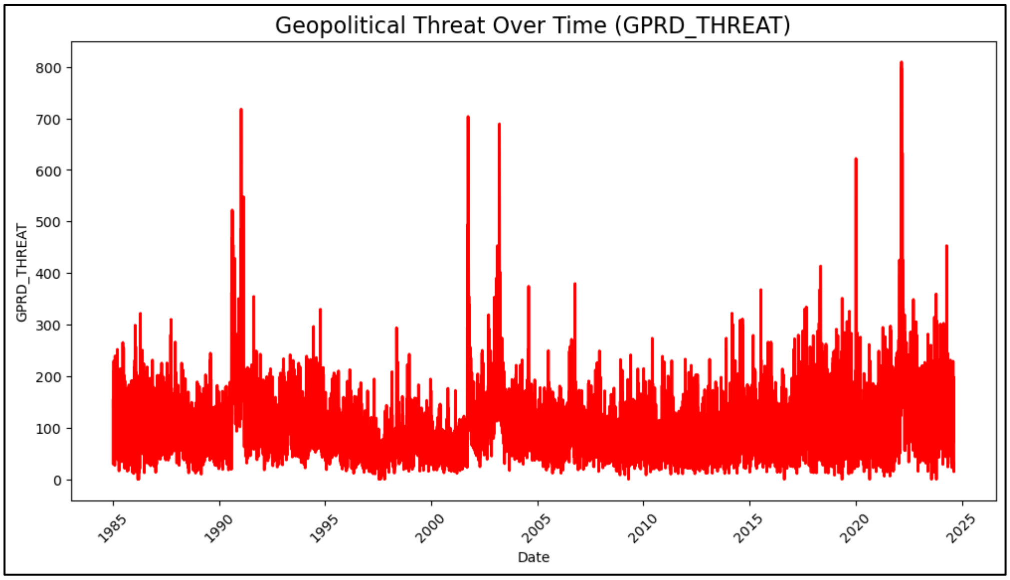

Figure 2: Depicts the Geopolitical Threat Overtime

The line chart above projects the fluctuations in geopolitical threat levels from 1985 to 2025. In this graph, the y-axis depicts the threat level and the x-axis reflects the time period. By observing this graph, one can notice a highly volatile trend with a lot of sharp peaks and troughs during the years. Several periods of sharply increased threat are describable, such as the early 1990s, mid-2000s, and around 2020. These peaks likely correspond to major events, crises, or policy shifts within some sort of geopolitical framework. While there is some variation with periods of relative stability, the longer-term trend appears upward, with a peak in geopolitical threat level abruptly higher than in previous years in 2025. This may reflect increasing instability around the world or the negative impact of new geopolitical threats.

Risk Factor Identification

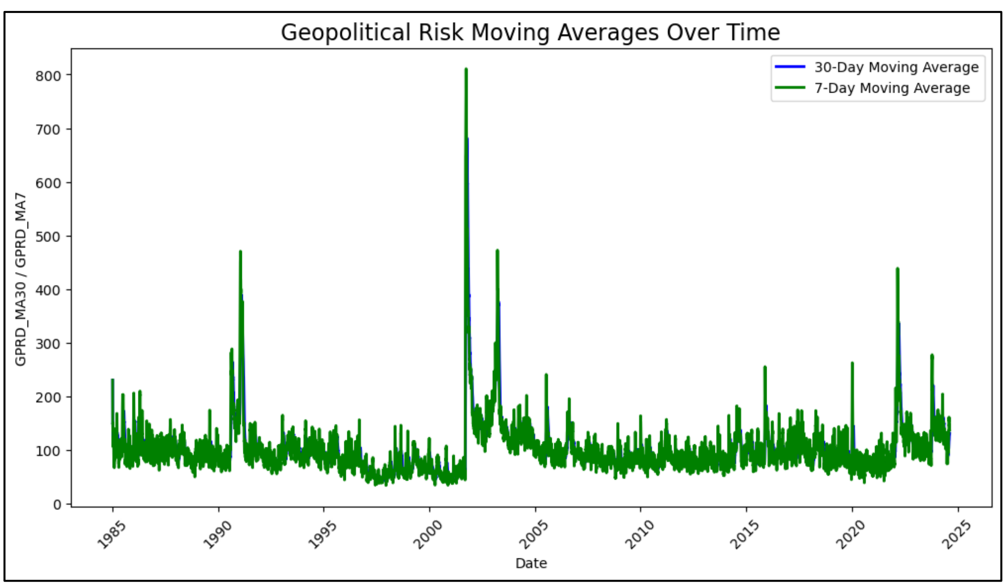

Figure 3: Exhibits Geopolitical Risk Moving Averages Over Time

The above line chart showcases the fluctuations of geopolitical risk levels between 1985 and 2025, according to the two moving averages: a 30-day moving average and a 7-day moving average. The y-axis is the risk level and the x-axis is the period. From this chart, it can be observed that the overall trend is highly volatile, with significant ups and downs for both moving averages during all these years. As one could expect, the 7-day moving average is more volatile than the 30-day one because of its greater sensitivity to short-run fluctuations. The same general trend can be assessed from both indicators: in the long run, geopolitical risk tends to increase, with an upward trend, especially during the late 2000s. This indicated upward tendency might be interpreted as increasing instability in the world or new emerging geopolitical problems.

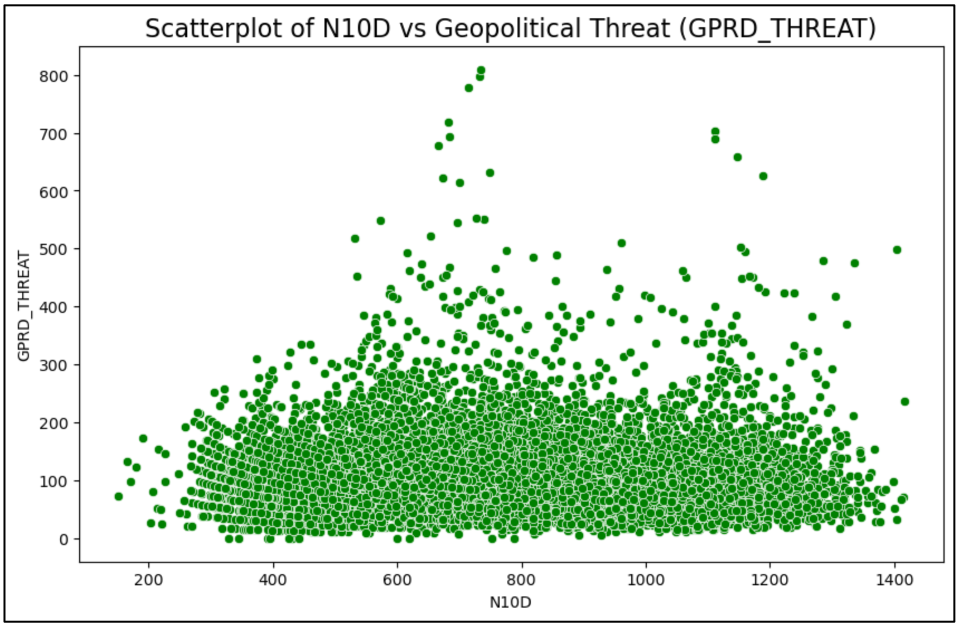

Figure 4:Portrays Scatterplot of N10D vs. Geopolitical Threat

This scatterplot shows the relationship between the variable N10D and geopolitical threat levels. For this scatterplot, the x-axis is represented by N10D, and the y-axis represents the threat level. The major observation to note is the generally positive correlation between the two variables represented in view; thus, higher geopolitical threat levels come with higher values of N10D. The linearity of the trend is not quite perfect due to the scattering of data points around the trend line. That implies, though N10D is a relevant variable to consider in the projection of geopolitical threat, there might as well be other variables coming into play. There are also a couple of outliers in the configuration of the data that might point to unusual events or circumstances in deviation from the general trend.

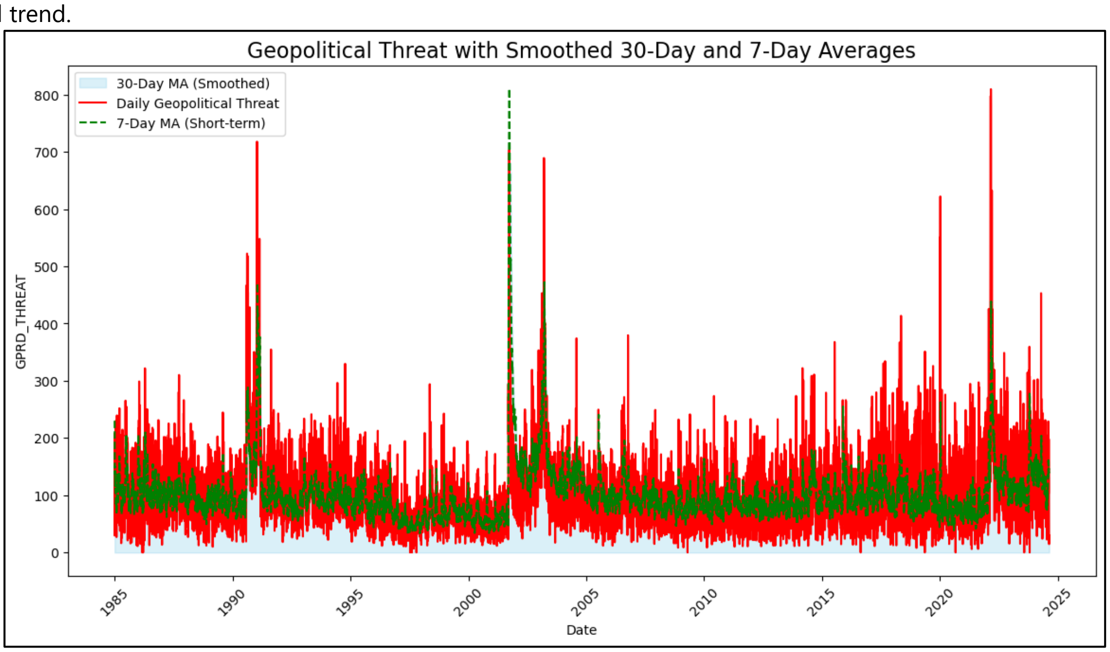

Figure 5: Exhibits Geopolitical Threat with Smoothed 30-Day and 7-Day Averages

The line graph above displays the fluctuations in the geopolitical threat level from 1985 to 2025, along with two smoothed moving average indicators: one is a 30-day and the other a 7-day moving average. The y-axis is the measure of the threat level, while the x-axis displays time. The general trend is rather volatile, represented by the two moving averages that have their ups and downs throughout the years. While the 7-day moving average is sensitive to short-run fluctuations and shows greater volatility, the 30-day moving average gives a smoother representation of the overall trend. Overall, geopolitical risk seems to build over time, according to the chart, though with periods of heightened tension and relative stability.

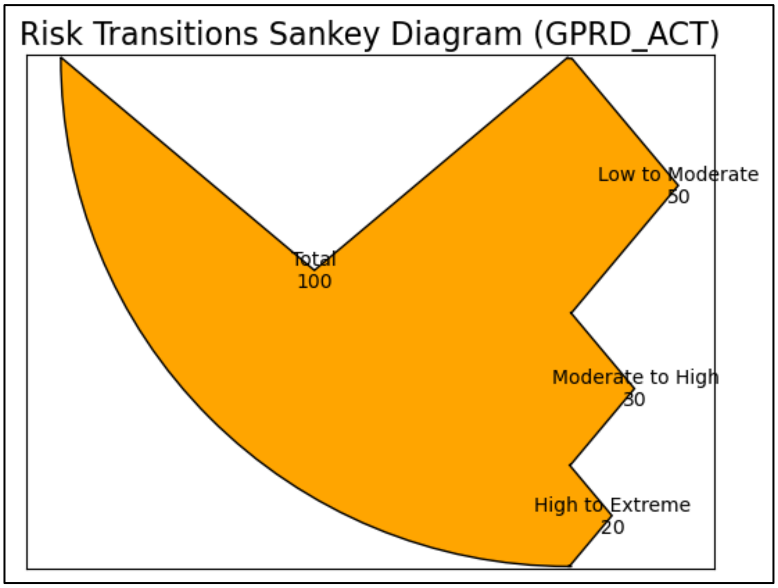

Figure 6: Showcases the Risk Transitions Sankey Diagram

The above Sankey diagram depicts transitions conducted over time from the beginning to the different ending levels of risk. It is a diagram comprising just one shape of the total amount of observations, 100, with three branches for Low entries transitioning into Moderate, Moderate to High, and High to Extreme, with 50, 30, and 20, respectively. The width of each branch is according to the proportion of observations that transitioned through it. This diagram shows that most transitions were in the low-to-moderate risk category, representing a generally stable risk environment. On the other hand, a sizeable minority fell into moderate-to-high categories, indicating higher chances of escalation. The number of transitions to the high-to-extreme risk category was lower at 20%, but it does point out the possibility of severe risk events. Contrarily, this diagram depicts the dynamics of risk visually and highlights possible upward and downward transitions.

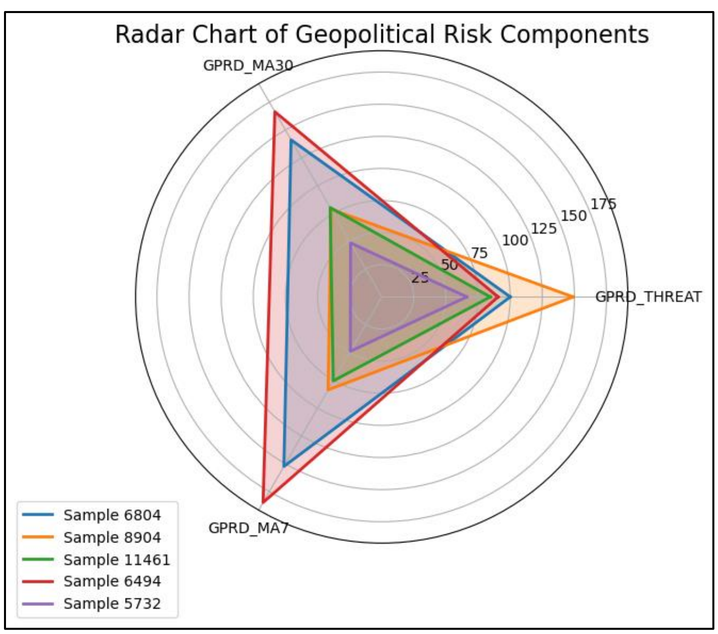

Figure 7: Depicts Radar Chart of Geopolitical Risk Component

This radar chart compares five samples, 6804, 8904, 11461, 6494, and 5732, for the three geopolitical risk components: GPRD_MA30, GPRD_THREAT, and GPRD_MAT. The value of each component is mapped to the radial scale so that higher values reflect greater risk. The overall profile of risk is outlined by connecting, with form polygons, the data points for each sample. Sample 6804 is the highest in all three components of risk, while Sample 5732 has the lowest. Sample 8904 shows a pretty high level of GPRD_MA30 and GPRD_THREAT but a relatively lower level of GPRD_MAT. By contrast, Sample 11461 exhibits a more moderate risk profile represented by a middle-of-the-scale for all three components. Sample 6494 shows an extremely unique pattern: its GPRD_MAT is high, but GPRD_MA30 and GPRD_THREAT are relatively low. Overall, the chart can visually compare the risk profiles among the five samples to show each of their strengths and weaknesses on various geopolitical risk factors.

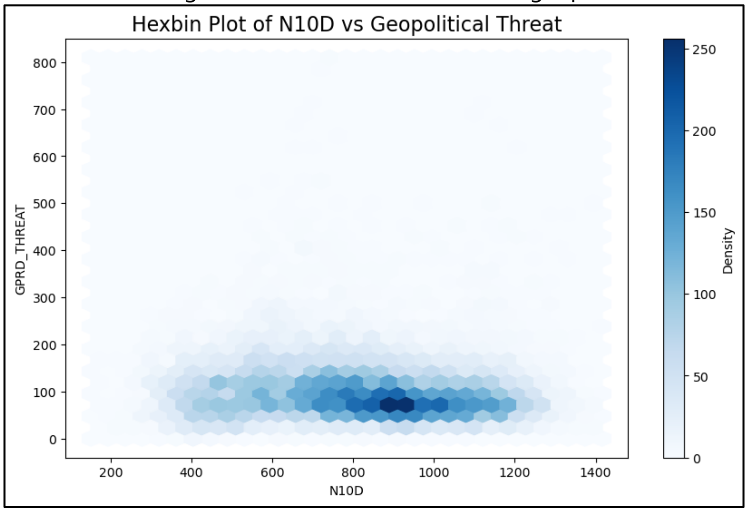

Figure 8 portrays the Hxbin Plot of N10D vs. Geopolitical Threat.

This Hexbin plot above examines the relationship between N10D and geopolitical threat level. The x-axis represents N10D, and the y-axis shows the threat level. Hexagonal bins are used to indicate the number of data points that fall into a region. The color gradient on the right-hand side of the plot represents the density. Overall, the plot shows a general positive correlation between the N10D and the geopolitical threat with, at the same time, the densest regions of data points clustering along a diagonal line from the bottom left to the top right of the figure. What follows from this plot, however, is that this exponential relationship is not without its aberrations; notice the scattering of data and differing density across different regions. This means that though N10D is an important factor in understanding geopolitical threats, it may not be the only one.

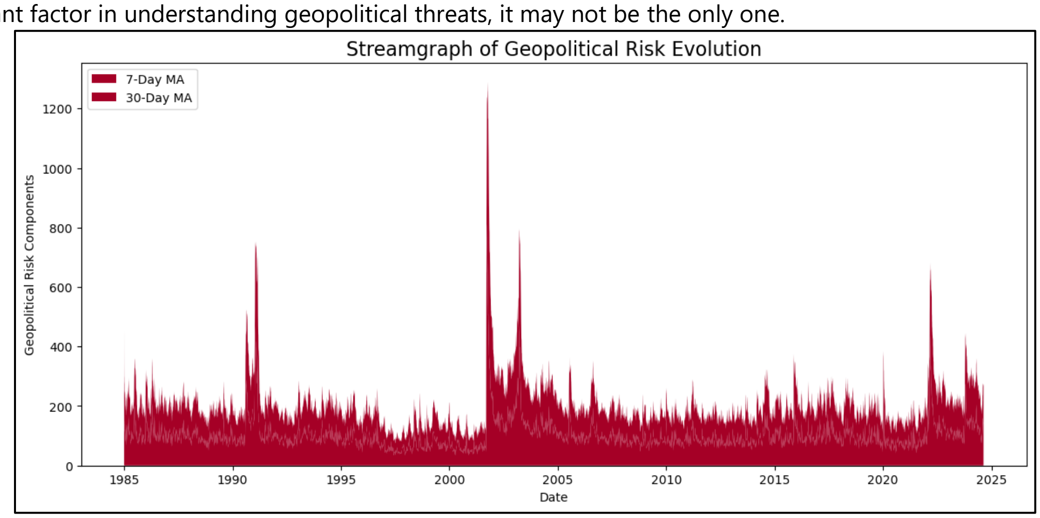

Figure 9: Displays Streamgraph of Geopolitical Risk Evolution

The presented streamgraph illustrates the fluctuation and flows of geopolitical risk levels from 1985 through 2025, along with two indicators of moving averages: a 7-day moving average and a 30-day moving average. The y-axis reflects the magnitude of risk, while the x-axis represents time. From the chart, it can be seen there has been a generally volatile trend, with both moving averages showing significant peaks and troughs over the years. Being more sensitive to temporary changes, the 7-day moving average then becomes highly volatile in comparison with the 30-day one, reflecting the general trend smoothened. The chart, in general, provides evidence of a gradual build-up in geopolitical risk over time, punctuated by periods of heightened tension and relative stability.

Economic Impact Assessment

Bouoiyour et al. (2021), state that global events, which are regarded as geopolitical risks including wars, political instability, and trade disputations, are considered to have their influences on the economies of the world. The United States, an economic superpower globally, is especially vulnerable concerning issues related to geopolitical risk since there are considerable networks of international trade and investment. Understanding the correlation between geopolitical risks and economic indicators in the United States is essential for policymakers, businesses, and investors alike.

Significant volumes of empirical studies have found robust negative relations between geopolitical risks and various economic indicators in the U.S. Increased geopolitical tensions are likely to be associated with heightened uncertainty, a decline in investor confidence, and disruption of trade flows. Each of these can hurt economic growth, employment, and consumer spending. To explicate, studies have proved that geopolitical tensions lower exports, raise import prices, and decrease business investment eventually (Caldara & Iacoviello, 2022). Moreover, geopolitical events cause turbulence in money markets that causes fluctuation in stock prices, interest rates, and exchange rates, which further deteriorates economic downturns. Some case studies that illustrate the economic consequence of geopolitical events in the U.S. are given below:

9/11 Attacks. The attack by terrorists in the United States of America on September 11, 2001, had a shattering effect on the economy of the United States of America. There was an immediate decline in consumer spending, a rise in unemployment, and a severe fall in the prices of stocks and shares immediately after the attacks (Kamruzzaman, 2022). Other long-term effects of the attacks included increased government spending on security, disruptions in international trade, and a decline in tourism. The U.S. economy eventually recovered from these shocks, but it showed that the country was very vulnerable to large-scale geopolitical events.

The 2008 Global Financial Crisis. While the immediate causes of the 2008 Global Financial Crisis were related to financial market failure, geopolitical factors played an indirect role in this process. This crisis also happened to fall during a period of high geopolitical tension in the Middle East and North Africa. There was, therefore, increased oil prices, further destabilizing the world economies (Li et al, 2024). With the crisis in the financial systems, the consequence on the economy of the United States was that there was a deep recession, whereas unemployment rates in the United States were high, and consumer confidence had fallen.

The COVID-19 Pandemic. Although not strictly a geopolitical event, the COVID-19 pandemic brought about dramatic economic effects both internally in the United States and globally. Lockdowns, supply chain disruptions, and a protracted decline in global trade have all ballooned as the virus spread. All these factors combined to ensure the steep economic slump in the U.S., marked by massive redundancies and a decline in consumer expenditure (Shawon et al., 2024). Whereas the economy of the United States has started recovering from the pandemic, the long-term economic implications are yet to be determined.

Model Performance

Model	MSE	R-Squared [R^2]
Random Forest	455.423	0.877
XG-Boost	439.189	0.881
Linear Regression	2107.098	0.431

Table 1: Showcases Model Performance Summary

Comparative Analysis

The Linear Regression model variance captured a moderate proportion of the variance in the dataset: R^2 = 0.431, suggesting that the dependence between features and GPRD_THREAT is probably nonlinear. Subsequently, the Random Forest model outperformed Linear Regression with its R^2 value of 0.877, which means the model could capture a large proportion of the variance in the target variable. XG-Boost outperformed Random Forest slightly, with the lowest MSE and the highest R^2 value. However, both Random Forest and XG-Boost proved to be suitable methods for this kind of dataset since they model the non-linear relationship and interaction between the features. Among all the models, the best performance was that of XG-Boost; it had the lowest MSE and highest R^2: 0.881. Thus, XG-Boost is the best model fitted for the prediction of GPRD_THREAT, probably because of its robust optimization and also its capability to capture a lot of complicated patterns in data.

V. Discussion

Insights and Implications

The main findings that have been derived through the comparative analysis of different machine learning models were curated and deployed to predict the level of geopolitical threat in the United States as follows: The prediction of geopolitical risk is an extremely complex task; The nature of relationships among feature and target variables is highly nonlinear and complicated, hence the process of predicting the threat level becomes tough. Overall, the results demonstrated by the ensemble methods, such as Random Forest and XG-Boost, were far superior to those of the Linear Regression model. This indeed confirms the advantages of these algorithms in extracting complex patterns and interactions that the same data might have. Although XG-Boost turned out to be the best model analyzed in this exercise, surely there is room for even more experimentation and refinement. Further fine-tuning could be done by trying other hyperparameters or selecting other features; one could even use more advanced techniques such as deep learning, which may yield even better results.

For policymakers:

Informed decision-making. Accurate forecasting of geopolitical threat levels can therefore provide a clear basis upon which policymakers rely in decisions about foreign policy and defense spending, and even economic development. Understanding the specifics of geopolitical risk allows policymakers to craft better strategies for reducing threats and ensuring stability.

Early warning systems. This outcome can be accomplished by forming correct predictive models that have to assist policy thinkers in establishing an early warning system, which would trigger an alarm in case there is probably going to be a geopolitical crisis. Time is very valuable during which efforts at preventing such an event are made, thereby reducing its negative impacts significantly.

Resource allocation. From this analysis, glimpses can show policymakers the way forward in resource allocation against geopolitical threats. Understanding the risks and what drives these risks allows policymakers to focus on areas of high need.

For USA Businesses:

Risk Management. The geopolitical threat level perceived using the proposed models will enable business organizations to identify and manage risks that may affect the operations of the business organizations. Companies can, therefore, understand factors that contribute to risk and develop contingency plans, enabling them to take proactive measures to mitigate negative impacts from geopolitical events.

Supply Chain Resilience. Predictive models will help businesses estimate the potential risks to their supply chains and create strategies for mitigating any disruptions that might come through geopolitical events. This may be by diversification of suppliers, investing in alternative sourcing options, or establishing contingency plans in case of supply chain disruption.

Investment decisions. Through the insights from the analysis, businesses in the U.S. can make intelligent investment decisions. The rationale is that foreign investors can only invest in a country where the economic impact of a geopolitical event is favorable and not severe.

Limitations and Challenges

Lack of data quality and availability: Good quality full-scale data on geopolitical events and their corresponding economic indicators may be hard to obtain. Moreover, data availability could be duration- and region-specific, which limits the scope of analysis.

Data bias: There is the possibility of biases within the analyzed data, such as selection bias or measurement error. The biases then affect the accuracy and generalization of the results themselves.

Model complexity: The construction of accurate predictive models about geopolitical risk is very time-consuming and requires strong computational efforts and special expertise. The complications of the models could make them hard to interpret and explain.

Limitations of the Present Study and its Model

Limited scope: The model in this given study is explored for a certain number of features and models. The analysis with other features and models may give different results in their ways.

Time horizon: The analysis was mostly based on historical data and may not be able to accurately capture future geopolitical events. Besides, the dynamics of geopolitical risk can alter over time, and new factors may surface that are not captured in the current dataset.

Uncertainty: Forecasting geopolitical incidents is inherently uncertain, and there is always the possibility of unanticipated occurrences that cannot be accurately expected. The models used in this analysis provide probabilistic predictions, which should be interpreted with caution.

Recommendations

Mitigation Strategies

Improved Intelligence Gathering and Analysis: The U.S. government should consider Investing in strong intelligence gathering and analysis algorithms such as the XG-Boost models that will enable the identification of emerging geopolitical threats and the evaluation of their potential economic consequences.

Diversification and Resilience: The government should enact policies that allow diversification of the economy and its resilience to minimize its vulnerability to geopolitical external shock. This will be achieved by fostering domestic industries, encouraging foreign direct investment, and strengthening trade relationships with a diverse range of partners.

Strategic Engagement: This quest would mean active diplomatic and international cooperation on geopolitical tensions to bring about stability. It also involves engaging in multilateral forums, the negotiation of agreements on conflict resolution, and humanitarian assistance.

Investment in Security and Surveillance: The U.S. government should channel sufficient amounts on national security and infrastructure resilience to mitigate any potential economic consequences of geopolitical events. This would involve investment in cybersecurity, critical infrastructure protection, and emergency response capabilities.

Conclusion

The prime objective of this study was to analyze the impact of geopolitical events on the U.S. economy, to identify key risk factors and their economic implications as well as propose strategies for mitigating adverse effects. Datasets used in this exploration were collected from different reliable sources to assess sources of geopolitical risk data and their economic impact on the U.S. First, data on geopolitical risk were collated from a combination of real-time news reports, government databases, and international organizations involved in monitoring geopolitical events. Key sources for this included GDELT news and sentiment data, official reports from U.S. government agencies such as the Department of State and the Department of Defense about foreign policy, conflict, and security, while major financial news outlets like Bloomberg and Reuters provided moment-by-moment coverage of events in the geopolitical sphere. We applied the Geo-Risk-Regressor model, a form of multimodal design to predict geopolitical threats arising from economic indicators, real-time news sentiment, and government reports on geopolitical events. The Geo-Risk-Regression Model is an integrated set of machine learning algorithms, from time-series and NLP to econometric regression, on structured and unstructured data comprising economic indicators, real-time news sentiment, and government reports on geopolitical events. A rigorous structured procedure was followed in implementing the Geo-Risk-Regressor to analyze the economic impact of geopolitical risks in the U.S. To assess and evaluate the performance of the algorithms, two key performance evaluation metrics were utilized MSE & R-squared. Among all the models, the best performance was that of XG-Boost; it had the lowest MSE and highest R^2. Thus, XG-Boost is the best model fitted for the prediction of GPRD_THREAT, probably because of its robust optimization and also its capability to capture a lot of complicated patterns in data. The geopolitical threat level perceived using the proposed models will enable business organizations in the USA to identify and manage risks that may affect the operations of the business organizations. Companies can, therefore, understand factors that contribute to risk and develop contingency plans, enabling them to take proactive measures to mitigate negative impacts from geopolitical events. Predictive models will help businesses in America estimate the potential risks to their supply chains and create strategies for mitigating any disruptions that might come through geopolitical events.

References

[1] Ahmad, M., Ali, M. A., Hasan, M. R, Mobo, F. D., & Rai, S. l. (2024). Geospatial Machine Learning and the Power of Python Programming: Libraries, Tools, Applications, and Plugins. In Ethics,

[2] Al Mukaddim, A., Mohaimin, M. R., Hider, M. A., Karmakar, M., Nasiruddin, M., Alam, S., & Anonna, F. R. (2024). Improving Rainfall Prediction Accuracy in the USA Using Advanced Machine Learning Techniques. Journal of Environmental and Agricultural Studies, 5(3), 23-34.

[3] Bouoiyour, J., Selmi, R., Hammoudeh, S., & Wohar, M. E. (2021). What are the categories of geopolitical risks that could drive oil prices higher? Acts or threats? *Energy Economics*, *84*, 104523.

[4] Buiya, M. R, Laskar, A N., Islam, M. R., Sawalmeh, S. K. S., Roy, M. S. R. C., Roy, R. E. R. S., &Sumsuzoha, M. (2024). Detecting IoT Cyberattacks: Advanced Machine Learning Models for

[5] Enhanced Security in Network Traffic. Journal of Computer Science and Technology Studies, 6(4),142-152.

[6] Caldara, D., & Iacoviello, M. (2022). Measuring geopolitical risk. American Economic Review, 112(4), 1194-1225.

[7] Debnath, P., Karmakar, M., Khan, M. T., Khan, M. A., Al Sayeed, A., Rahman, A., & Sumon, M. F. I. (2024). Seismic Activity Analysis in California: Patterns, Trends, and Predictive Modeling. Journal of Computer Science and Technology Studies, 6(5), 50-60.

[8] Dogan, E., Majeed, M. T., & Luni, T. (2021). Analyzing the impacts of geopolitical risk and economic uncertainty on natural resource rents. *Resources Policy*, *72*, 102056.

[9] Gong, X., & Xu, J. (2022). Geopolitical risk and dynamic connectedness between commodity markets. *Energy Economics*, *110*, 106028.

[10] Islam, M. R., Nasiruddin, M., Karmakar, M., Akter, R., Khan, M. T., Sayeed, A. A., & Amin, A. (2024). Leveraging Advanced Machine Learning Algorithms for Enhanced Cyberattack Detection on US Business Networks. Journal of Business and Management Studies, 6(5), 213-224.
[11] Kamruzzaman, M. M. (2022). Impact of social media on geopolitics and economic growth: Mitigating the risks by developing artificial intelligence and cognitive computing tools. *Computational Intelligence and Neuroscience*, *2022*(1), 7988894.
[12] Khan, M. A., Rahman, A., & Sumon, M. F. I. (2023). Combating Cybersecurity Threats in the US Using Artificial Intelligence. International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 14(1), 724-749.
[13] Li, H., Ali, M. S. E., Ayub, B., & Ullah, I. (2024). Analyzing the impact of geopolitical risk and economic policy uncertainty on the environmental sustainability: evidence from BRICS countries. *Environmental Science and Pollution Research*, *31*(34), 46148-46162.
[14] Nasiruddin, M., Al Mukaddim, A., & Hider, M. A. (2023). Optimizing Renewable Energy Systems Using Artificial Intelligence: Enhancing Efficiency and Sustainability. International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 14(1), 846-881.
[15] Rahman, A., Karmakar, M., & Debnath, P. (2023). Predictive Analytics for Healthcare: Improving Patient Outcomes in the US through Machine Learning. Revista de Inteligencia Artificial en Medicina, 14(1), 595-624.
[16] Reivan-Ortiz, G. G., Cong, P. T., Wong, W. K., Ali, A., Thu, H. T. T., & Akhter, S. (2023). Role of geopolitical risk, currency fluctuation, and economic policy on tourist arrivals: temporal analysis of BRICS economies. *Environmental Science and Pollution Research*, *30*(32), 78339-78352.
[17] Shawon, R. E. R., Rahman, A., Islam, M. R, Debnath, P., Sumon, M. F. 1., Khan, M. A., & Miah, M. N. l. (2024). A1-Driven Predictive Modeling of US Economic Trends: Insights and Innovations. Journal of Humanities and Social Sciences Studies, 6(10), 01-15.
[18] Shahzad, U., Ramzan, M., Shah, M. I., Doğan, B., & Ajmi, A. N. (2022). Analyzing the nexus between geopolitical risk, policy uncertainty, and tourist arrivals: evidence from the United States. *Evaluation Review*, *46*(3), 266-295.
[19] Sumon, M. F. 1., Osiujjaman, M., Khan, M. A., Rahman, A., Uddin, M. K., Pant, L, & Debnath, P. (2024). Environmental and Socio-Economic Impact Assessment of Renewable Energy Using
[20] Machine Learning Models. Journal of Economics, Finance and Accounting Studies, 6(5),112-122.
[21] Sumon, M. F. I., Khan, M. A., & Rahman, A. (2023). Machine Learning for Real-Time Disaster Response and Recovery in the US. International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 14(1), 700-723.
[22] Sun, X., Gao, J., Liu, B., & Wang, Z. (2023). Big data-based assessment of political risk along the Belt and Road. *Sustainability*, *13*(7), 3935.
[23] Zeeshan, M. A. F., Sumsuzoha, M., Chowdhury, F. R., Buiya, M. R, Mohaimin, M. R., Pant, L, &
[24] Shawon, R. E. R. (2024). Artificial Intelligence in Socioeconomic Research: Identifying Key Drivers of Unemployment Inequality in the US. Journal of Economics, Finance and Accounting Studies, 6(5),54-65.
[25] Shawon, R. E. R., Miah, M. N. I., & Islam, M. Z. (2023). Enhancing US Education Systems with AI: Personalized Learning and Academic Performance Prediction. International Journal of Advanced Engineering Technologies and Innovations, 1(01), 518-540.
[26] Shil, S. K., Islam, M. R., & Pant, L. (2024). Optimizing US Supply Chains with AI: Reducing Costs and Improving Efficiency. International Journal of Advanced Engineering Technologies and Innovations, 2(1), 223-247.
[27] Shil, S. K., Chowdhury, M. S. R., Tannier, N. R., Tarafder, M. T. R., Akter, R., Gurung, N., & Sizan, M. M. H. (2024). Forecasting Electric Vehicle Adoption in the USA Using Machine Learning Models. Journal of Computer Science and Technology Studies, 6(5), 61-74.