Hungarian University of Agriculture and Life Sciences

The Thesis of the PhD dissertation

COUNTRY RISK ASSESSMENT IN MULTI-NATIONAL CORPORATIONS

Doctoral (PhD) dissertation

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Kaposvár, Hungary

2026

Hungarian University of Agriculture and Life Sciences

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List of Abbreviations

AI	Artificial Intelligence
AIG	American International Group
ALEG	Allianz Trade Country Risk Atlas
ANN	Artificial Neural Network
API	Application Programming Interface
ACU	Area Under the ROC Curve
BANI	Brittle – Anxious – Non-Linear – Incomprehensible
BERI	Business Environment Risk Intelligence
BOP	Balance of Payments
BRICS	Brazil, Russia, India, China, South-Africa
CAST	Conflict Assessment System Tool
CC	Credit Classification
CEO	Chief Executive Officer
COVID-19	Coronavirus Disease 2019
CR	Country Risk
CRAT	Country Risk Assessment Tool
CRC	Country Risk Classification
CSR	Corporate Social Responsibility
CSS	Cascading Style Sheets
DNI	Director of Intelligence
DNN	Deep Neural Network
ECB	European Central Bank
EIU	Economist Intelligence Unit
ESG	Environmental, Social, and Governance
EXIM	Export-Import Bank
FCPA	Foreign Corrupt Practices Act
FDI	Foreign Direct Investment
GATT	General Agreements on Tariffs and Trade
GDP	Gross Domestic Product
GNP	Gross National Product
GPR	Geo-Political Risk
HTML	Hypertext Markup Language

ICRG	International Country Risk Guide
IMF	International Monetary Fund
IP	Internet Protocol
IPI	International Peace Institute
JSON	JavaScript Object Notation
LDC	Less Developed Countries
LIME	Local Interpretable Model-Agnostic Explanations
LNG	Liquefied Natural Gas
MIGA	Multilateral Investment Guarantee Agency
MINORA	Multicriteria Interactive Ordinal Regression Analysis
ML	Machine Learning
MNC	Multinational Corporations
NEXI	Nippon Export and Investment Insurance
NIEO	New International Economic Order
NN	Neural Network
OECD	Organization for Economic Co-operation and Development
OPEC	Organization of the Petroleum Exporting Countries
OSINT	Open-Source Intelligence
PESTEL	Political, Economic, Social, Technological, Environment, Legal
PMI	Purchasing Managers Index
PRI	Political Risk Insurance
PRS	Political Risk Service
PSSI	Political, Security and Socioeconomic Instability Index
RF	Random Forest machine learning model
S&P	Standard & Poor’s
SC	Standard Chartered
SHAP	Shapley Additive Explanations
TNC	Transnational Corporation
UKBA	United Kingdom Bribery Act
UNCTAD	United Nations Conference on Trade and Development
VE	Vulnerability Exercise
WEF	World Economic Forum
WTO	World Trade Organization
VUCA	Volatility – Uncertainty – Complexity – Ambiguity

1. INTRODUCTION

Country risk assessment is an interdisciplinary field that endeavors to evaluate a complex array of political, societal, and environmental risks that are often difficult to identify. While generally country risk assessment has multiple fields of application, this work concentrates on the role of country risk assessment in multinational corporations (MNCs). Numerous scholars of different disciplinary facets of the field have been examining old and new models over the past decades, but many challenges of country risk modeling remain unresolved. A query concerning the methodology of risk models persists, specifically whether quantitative or qualitative models are more appropriate to assess country risk.

MNCs, analysts, and scholars use country risk to collectively assess the hazards associated with foreign commercial operations that may be encountered, while the MNC is active in the host country. The modelling of country risk likely encompasses political, economic, and environmental risks. The definition of country risk has been interpreted in various ways throughout the history of academic research. According to Gaillard (2020), the challenge in defining country risk arises from the differing concerns of country risk managers. An export-oriented risk manager will have different priorities than a foreign credit risk manager. Additionally, Gaillard highlights the issue of the numerous country risk indicators developed by scholars, each bringing diverse methodologies, reports, and ratings. He aligns with the definition provided by Bouchet et al. (2003), which describes country risk as encompassing any macroeconomic, microeconomic, financial, social, political, institutional, judicial, climatic, technological, or sanitary risk that affects (or could affect) an investor in a foreign country. Potential risks can manifest in various forms: financial losses, threats to the safety of the investing company's employees, clients, or consumers, reputational damage, or loss of a market or supply source. Gaillard identifies the primary business activities related to country risk as trade and investment, stating, „At the international level, trade consists of importing and exporting goods and/or services. Lending involves a bond purchase or loan agreement with a (public or private) foreign borrower." Gaillard traces the concept of country risk back to Frederick Dahl in 1967. Dahl, who was then an assistant director of the division of examinations at the Board of Governors of the US Federal Reserve, noted that the key difference between domestic and international lending is the need to evaluate country risk. Sottilotta (2013, 2016) recently accumulated the variety of definitions of country risk again.

In this research, risk is defined as an adverse impact on the business operations of a multinational corporation (Bouchet et al., 2003). Historically, periods of elevated geopolitical risk served as the foundation for defining and analyzing country risk. For numerous key political events examined, the underlying cause of the risk was discerned and elucidated by statistical analysis or expert opinion. Country risk models incorporate characteristics that indicate which hazards may adversely affect business operations.

Recently, country risk assessment, or country analysis, has experienced a revival due to the increasing sensitivity of the hyperlinked global business environment to political turbulence and other aspects of country risk. While the first country and political risk models had military applications, their demand surged in the commercial sector starting in the 1970s.

Although country risk has consistently been a topic of ongoing academic research, the events of this decade—especially the Russia-Ukraine conflict—have led to increased academic inquiry. As a result, researchers continue to develop numerous models, most of which lack universal relevance to multinational corporations. Academic research frequently examines only a limited number of country risk factors, failing to provide a comprehensive framework for companies to evaluate their individual country risk. This is primarily due to the missing regression between country risk variables, which are often overlapping in models and have unequal relevance to MNCs' foreign operations.

Certainly, since a definitive prediction of the future is unattainable, a perfect model for assessing country risk will never exist. Nonetheless, the domain of country risk assessment is seeing a significant resurgence, driven by international uncertainties, geopolitical transformations, and a politically multipolar globe. This thesis develops new approaches and review existing ones. Novel machine learning (ML) methodologies have recently enhanced this process.

In the past, efforts to replicate country risk assessments from institutions and specialized expert evaluations were successful; however, the results were always retrospective, focusing solely on improving existing models or proprietary models developed by specialist country risk firms (Cosset et al., 1993). Furthermore, these reengineering efforts occurred inside academic research; they rarely considered the aspects of application and the incorporation of a country risk model inside a specific corporation. In the end, the development of country risk models failed to incorporate data from international firms, especially those of midsize multinational corporations.

1.1 Research Background

The spike in country risk research leads to the updating of older models and the ongoing exploration of new models, both of which are subjects of academic debate. Country risk variables may not have changed much due to the comprehensive apprehensions of risk factors previously researched, since their role has been reaffirmed historically. However, the manifestations of the risk and its roots are changing. Formerly marginalized risks, such as the earth's defined resource scarcity limitations, are now transforming into urgent political risks for multinational corporations. Geopolitical tensions and conflicts are intrinsic to country risk assessment; nevertheless, the scarcity of resources, coupled with an increasing global population and persistent demand, accentuates the risks associated with a finite planet (Meadows et al., 1972).

The Club of Rome Report titled „The Limits to Growth," published in 1972, addresses the finite planet problem and its implications for country risk assessment. This report outlines the effects of living on a finite planet across various domains, emphasizing the consequences of resource depletion, pollution, famine, and political conflict. The analysis suggests that the world is continuously moving toward a crisis, asserting, „The fundamental behavioral pattern of the world system is exponential growth of population and capital, succeeded by collapse" (Meadows et al., 1972). These issues of scarcity contribute to a challenging era of economic globalization, which will significantly impact multinational corporations.

Assessing globalization as a risk factor is challenging. Globalization complicates the causation and effects of all risk variables. Assessing the impact of an incident in a foreign country on any business operation is becoming increasingly challenging due to the complex interconnections of international relations across markets and states. The advancement of globalization has altered the economic landscape for multinational corporations, yielding both beneficial and detrimental effects for the world. Multinational corporations could meanwhile dominate markets and establish new ones by exporting their goods and services. Undoubtedly, multinational corporations faced challenges from emerging competition; yet, for Western corporations of this nature, the new markets abroad proved to be lucrative.

Global supply chains connect these extensively networked markets. As a result, new risks to supply chain continuity have emerged, driven by governmental intervention and other factors. The role of multinational corporations in the globalized world has frequently been criticized as a form of neocolonialism, raising concerns about detrimental political interference, including expropriation. Currently, the role of multinational corporations is under significant scrutiny, especially in Western nations (Bouchet et al., 2018). Conflicts, tensions, and various hostilities characterize the current global landscape for multinational corporations. A McKinsey survey reveals that business leaders view geopolitical conflict as the primary risk to economic growth. The result raises the question of whether the complexities of the existing conflicts can accurately represent the characterization of country risk variables. Moreover, conflicts that define country risk are present on all seven continents (McKinsey and Company, 2024).

The initial country and political risk models were primarily designed for military applications; however, their demand significantly increased in the commercial sector beginning in the 1970s, largely relying on expert opinions. Multinational companies, especially those based in the United States, experienced a stark realization of the need for these models after the Iranian Revolution led to the confiscation of their international assets, which coincided with the collapse of the foreign market for their products and services in Iran (Kennedy, 1987). Following the collapse of the Soviet Union, many multinational corporations aimed to capture market shares in the developing world's emerging markets, despite being aware of the inherent country risks. Although several developing nations established democratic frameworks, they continued to face ongoing political and economic instability, legal uncertainty, and the threat of political violence and social unrest, often under autocratic rule. This situation posed a constant risk of asset losses for multinational corporations, primarily due to the possibility of government interference (Kennedy, 1987). Consequently, researchers became more involved in the exploration and application of country risk models.

Some multinational corporations had in the past established teams to assess country risk within their organizations. As the global political landscape remains undefined and subject to change, these MNCs are beginning to revisit this practice, which had been largely dominated in recent decades by specialized consulting firms such as the PRS Group. As a result, researchers continue to develop numerous models for evaluating country risk, most of which are not universally applicable to all multinational corporations. Academic and institutionalized research often focuses on a limited range of country risk factors, resulting in a lack of a comprehensive framework for companies to assess their specific country risk. This limitation largely stems from the absence of a clear regression analysis between country risk variables, which often overlap in existing models and possess varying degrees of relevance to the foreign operations of multinational corporations (Cosset and Roy, 1991).

Certainly, since a definitive prediction of the future is unattainable, a perfect model for assessing country risk will never exist. Nonetheless, the field of country risk assessment is experiencing a significant resurgence. Recent advancements in machine learning methodologies have enhanced this process. Past efforts to replicate the country risk assessments conducted by institutions and specialized experts were successful, but the results were always retrospective, reflecting past events, and continued to improve only existing models or proprietary models developed by specialized firms that assess country risk (Cosset et al., 1993). Furthermore, these reengineering efforts were based on a proven selection of general applied country risk variables; however, they are rarely considered as outcomes of widespread open-source intelligence (OSINT) data application, which this thesis addresses. Ultimately, the country risk models were never designed to incorporate more timely data on country risk variables, especially for midsize multinational corporations that could benefit from short-term results.

Moreover, country risk models have not yet incorporated a monitoring function. In the model, the monitoring function could be a shorter time period during which data is collected, as is possible with OSINT. The Office of the Comptroller of the Currency (OCC) (2016), in its handbook, called for a country risk monitoring system that includes a process for recognizing when countries require elevated monitoring. Although these models were never explicitly designed for this purpose, such a function is necessary in a BANI (brittle-anxious-non-linear-incomprehensible) world. A multinational corporation operating in a foreign country faces varying degrees of exposure to this BANI environment (Cascio, 2020). In today’s global landscape, a corporation does not need to have any international operations to be susceptible to country risk, as illustrated by Bouchet et al. It will similarly be affected by the global economy. This situation underscores the interplay and complexity of micro-, macro-, and environmental risks in country risk assessments (Bouchet et al., 2003).

1.2 Problem Statement

The main issue addressed in this thesis is that previous country risk models, which incorporate multiple variables representing different aspects of country risk, face the challenge of non-linearity in their assessments. Even selected developments that affect country risk evaluations are rarely linear due to the sensitivity of various factors. Moreover, the same event that positively impacts one variable can have a detrimental effect on another. Consequently, the relationships are often non-linear, and quantitative methods, such as regression analysis, may omit important aspects of country risk analysis to achieve statistical significance (Cosset and Roy, 1991). Additionally, many published country risk models rely on proprietary information or data that is only published annually or quarterly, which complicates the creation of a universal or tailored country risk model for companies. Although multinational corporations operate in this information age, finding and implementing relevant data for the model can be challenging. The issue with open-source intelligence data lies in the difficulty of locating, wrangling, and managing the large volumes of data required for analysis.

To create an effective risk assessment function, new models must integrate data that outlines the macroeconomic and political landscape of a company operating in any host nation within a short time frame while still producing a comprehensive and statistically relevant model. Such an effort requires addressing the challenge of non-linearity in political issues and the lack of equilibrium in various countries and their societies. Regardless of the best approach to tackle these challenges—whether qualitative or quantitative—the non-linearity of country risk remains the primary obstacle for every model.

This research examines the potential of collecting open-source intelligence data and employing methods such as sentiment analysis and neural networks, which are increasingly used in artificial intelligence research and applications, to tackle the non-linearity problem associated with country risk. The study aims to investigate the following questions:

1. Can a single multinational corporation develop and implement its own risk assessment model to evaluate the country risk level in any of its host nations?
2. Is it feasible to gather the necessary amount of open-source intelligence data within limited time frames to ensure timely risk assessment?
3. Can neural networks, which have demonstrated promising results in both general economic applications and country-risk-specific tasks, utilize this open-source

intelligence data to create a country risk model capable of generating trend predictions?

4. Will this model yield significant results when evaluated using standard neural network testing methods such as LIME, SHAP, and K-fold analysis?

1.3 Research objectives and aims

This research examines the evolution of public data availability for model creation, acknowledging the common usability challenges associated with data collection. The data collection process is encapsulated by the term open-source intelligence, which includes all publicly accessible data from various sources. The model input derived from OSINT sources reflects the data used in the variables of previous country risk models, even though it is not explicitly designed for universal application in that context. To define OSINT, this research adopts the definition provided in the OSINT Strategy 2024-2026 report by the Director of National Intelligence: „OSINT is intelligence derived exclusively from publicly or commercially available information that addresses specific intelligence priorities, requirements, or gaps" (Office of the Director of National Intelligence, 2024b).

The appropriate timeframe for collecting data also needs to be considered. This research posits that nation risk assessment for corporations, in relation to corporate and macroeconomic data, should occur daily, weekly, or monthly. Currently, numerous data streams in country risk models rely on quarterly or annual data, rendering them inefficient for companies and a constant monitoring of country risk. This thesis assumes that, for a contemporary risk model, a data collection process involving only monthly data or longer is insufficient. Therefore, this research aims to collect data on a daily basis whenever possible. Country risk variables represent the intersection between qualitative checklist methodologies and quantitative techniques. Regression analysis and numerous quantitative methodologies exist for country risk models that warrant further investigation; however, it is posited that neural networks may effectively facilitate sentiment analysis, trend analysis, and prediction, thereby enhancing the speed and efficacy of identifying threats arising from political shifts or societal hostility toward the company (Cooper, 1999).

The elements of country risk have primarily been examined in isolation, and few country risk models attempt to integrate them inclusively. Additionally, the emerging use of open-source intelligence data collection and machine learning techniques in country risk assessment remains underexplored within the broader academic context. This work seeks to make a modest contribution to this fascinating field of country risk research. As Python has become a leading programming language for machine learning and artificial intelligence libraries, the next generation of quantitative country risk researchers has significant opportunities to develop machine learning applications for assessing country risk. This research also integrates libraries like TensorFlow and Keras within a R programming language environment (as outlined in Figure 6 and Appendix 8.3). Therefore, this thesis aims to create a model for assessing country risk that leverages these newly accessible data streams and methodologies, addressing the question if a universally applicable country risk model for multinational corporations can be developed.

1.4 Research hypothesis

The research background and problem statement led to the formulation of the hypotheses. If the country risk model developed in this thesis can be applied by multinational corporations to every country in the world, utilizing neural networks and individually collected OSINT data, and doing so without the need for expert opinions or external quantitative input on a daily basis, the findings would support the proposed hypotheses (as outlined in Table 1 below).

Hypotheses	
H1.	A neural network analysis framework can be developed for the purpose of country risk assessment utilizing individual collected daily open-source intelligence data that give a significant trend prediction.
H1.1	The proposed neural network demonstrates statistically significant predictive performance, as evidence by model interpretability techniques such as LIME (Local Interpretable Model Agnostic Explanations), SHAP (Shapley Additive Explanations) and the results of a K-fold analysis.
H1.2	The model effectively addresses and overcomes the limitations of linear assumptions inherent in traditional quantitively country risk assessment methodology.
H2.	The model will perform better in one-day-ahead predictions than in weekly and monthly predictions.

Table 1. Hypotheses of the study / Source: Author elaboration (2025)

1.5 Research framework

The central concept of this research involves the daily collection of open-source intelligence data from five exemplary countries to assess the risks associated with each country through sentiment analysis. The findings from this analysis will serve as the foundation for a trend analysis conducted using a deep neural network. The open-source intelligence data is categorized into seven variables, which are developed by merging variables from prior research. Established frameworks of country risk were utilized to formulate these variables, and the choice of neural networks as a quantitative method is informed by their successful application to economic issues (Cooper, 1999) and the contemporary interest in leveraging artificial intelligence to explore longstanding questions, such as a universal country risk model.

It is anticipated that the research hypothesis will yield significant results, leading to the development of a model that can be refined further. However, the outcomes of this study will be constrained by the availability of data, as the collected open-source intelligence varies in scope for each selected country. The variables aim to create a comprehensive framework that encompasses all sources of conflict within a country.

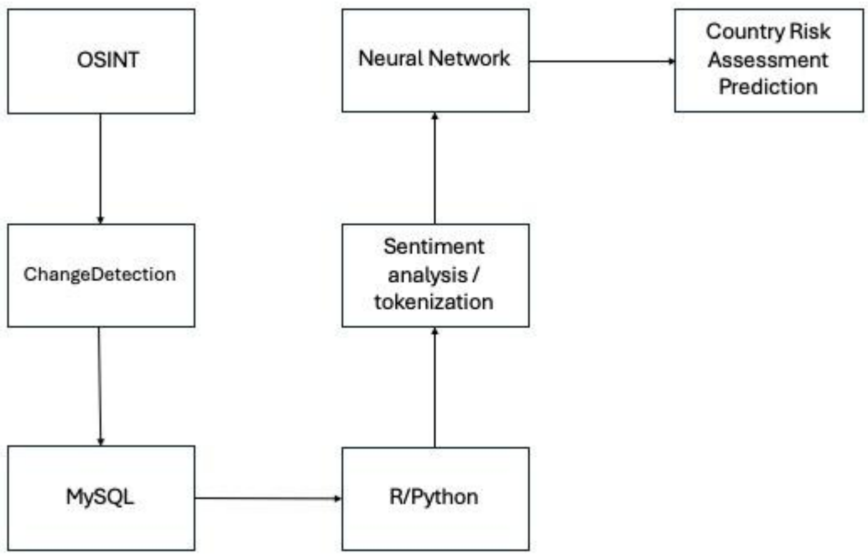

Figure 1. Research Framework *Source*: Author

1.6 Motivation and contribution of the research

The motivation for this research is to develop a universally applicable country risk model that can be implemented by any multinational corporation, regardless of its home country or the host countries in which it operates. While all multinational corporations (MNCs) require country risk assessments for their business operations, not all have the financial means to purchase external institutional country risk assessments. Furthermore, external institutional providers cannot always deliver the level of individualized assessment that MNCs require for their specific operational contexts. In addition, some MNCs require more timely risk assessments than institutional providers can offer, as such assessments are often updated only on a quarterly basis.

This objective will be achieved by utilizing modern machine learning techniques and innovative methods to collect country risk data. The research has established a data collection and processing framework, which aims to provide a modest perspective on the potential these approaches can offer. Regardless of the hypothesis's outcome, this work seeks to make a meaningful contribution to the field by advancing the next steps in country risk assessment.

2. LITERATURE REVIEW

The last century, along with recent history, provides numerous examples of country risk impacting multinational corporations and their operations worldwide. However, this literature review does not aim to compile a collection of case studies. Instead, it offers a brief overview of key works in the field of country risk assessment, highlighting how the literature has evolved. Given the extensive range of potential risks, the field has historically divided into multiple specialized research areas, spanning from qualitative political risk assessment to highly quantitative portfolio risk theory that addresses country risk. This complexity can be overwhelming for those interested in political matters. Therefore, this literature review will outline the progression that led to the model developed in this thesis.

Stefan H. Robock (1971) made a significant contribution to the research field of political risk in his paper titled „Political Risk: Identification and Assessment." Scholars researching political and country risk consistently reference his work. Primarily qualitative, the research emphasized the importance of political risk and the lack of awareness surrounding it among managers of multinational corporations. Robock effectively outlined the substantial impact such risks can have on business operations in host countries and challenged managers to develop techniques for forecasting political risk. This can now be extended to the challenge of the broader issue of identifying country risk.

Robock accurately noted that MNCs encounter political risk not only in developing countries, often referred to as less developed countries (LDCs) at the time of publication, but also in industrialized nations such as the USA and Sweden. He defined political risk operationally as „political risk in international business exists (1) when discontinuities occur in the business environment, (2) when they are difficult to anticipate, and (3) when they result from political change." He differentiated between abrupt occurrences that signify a political event and continuous changes, a distinction that remains relevant today in broader country risk assessments.

Robock pointed out that political scientists debated the definition of political instability, such as revolution. In both political risk and country risk, clear definitions are crucial for constructing a model framework. Additionally, he highlighted the challenges in separating political from economic risks, noting, „Political uncertainties in some nations have stimulated large outflows of flight capital, which in turn caused a balance of payments crisis." Robock also introduced one of the first distinctions between macro risk and micro risk, which will be discussed further in sections 2.3.2 and 2.3.1, respectively.

He tasked managers with the responsibility of understanding the potential intermingling of political and economic motivations and urged them to look beyond political decisions to uncover underlying forces. The potential consequences of political risk that Robock identified include „new operational restrictions, loss of transfer freedom, contract breaches and revisions, tax and other discriminatory policies, and damage to property and personnel [that] will change the operating environment for the international enterprise, usually in a negative way. Confiscation, expropriation, and, in some cases, contract breaches completely eliminate the feasibility of foreign operations."

Following Robock's research, many experts from diverse disciplines continued to build upon his findings. However, subsequent research on country risk and political risk increasingly focused on economic elements, leading to more refined modeling of macroeconomic aspects (Robock, 1971).

In 1993, J.C. Cosset et al. published a study titled „Replicating Country Risk Ratings," which demonstrated their ability to reproduce the country risk ratings from the publication The Institutional Investor. They built upon the research of Feder and Uy, which explained seventy percent of the variance in institutional investors' ratings for 55 countries by utilizing a set of economic indicators and two dummy variables for oil-exporting versus non-oil-exporting countries, as well as for countries that have experienced political turmoil versus those that have not. The Institutional Investor relied on specialists and proprietary data to derive its ranking outcomes. Cosset et al.'s mathematical programming model (MP) enabled the extraction of variables from publicly accessible institutional data. Additionally, the MP approach offers several attractive features; unlike logistic regression techniques, it accounts for the heterogeneous nature of countries by allowing different statistical relationships across them. Their research supports the notion that country risk models should integrate both new quantitative methods of data analysis and innovative data collection processes, whether for existing variables or for the creation of new ones.

Important for scholars as a country risk indicator has always been the level of foreign direct investment (FDI) a country has, both inflowing and outflowing. FDI is also of interest to a new generation of country risk researchers, such as Hassan (2022), Platona (2021, 2022), Wang

(2021), and Osabuohien-Irabor and Drapkin (2022). The rise in foreign direct investments closely links the globalization effect to the development of country risk research. Institutional investors and other multinational corporations grew increasingly concerned about their FDI in emerging markets, as these investments were often vulnerable to unstable democratic governments that introduced new or shifted various political, economic, and social policies. Recent research by Hassan (2022) reaffirmed the correlation. However, foreign direct investment (FDI) in developed countries also remains vulnerable to stand alone political risk (Baek and Qian, 2011). Both academic scholars and institutional researchers sought ways to mitigate these risks based on their models. However, research findings often revealed ambiguity regarding the effectiveness of country risk assessments. Oetzel et al. (2001) found that many business risk evaluations fail to predict crisis events related to FDI, stating that „results suggest that widely used risk measures provide little useful assistance in predicting any significant crisis". For instance, during the period when FDI increased fivefold from 44 billion US dollars to 243 billion US dollars between 1990 and 1996, countries like Mexico, which attracted 80% of private investment in Latin America, experienced a currency crash in 1994. Other nations that received FDI also faced similar political and economic crises. However, their research concentrated on „revolutionary events" characterized by currency fluctuations greater than 10%. Their study criticized existing country risk measures for their inability to predict extreme events. The country measures they evaluated included Euromoney Magazine, Institutional Investor Magazine, the International Country Risk Guide (ICRG, see Figure 2), and the Political Risk Service (now known as BERI). Nonetheless, they did not invalidate earlier research by Robock (1971), Kobrin (1979), or Cosset and Roy (1991). They reinforced their findings by confirming their first hypothesis: that „country risk measures are capable of forecasting business risk during periods of gradual (or incremental) environmental change." They also validated their second hypothesis, which states that models cannot foresee events resulting in a negative 40% change in currency value. They concluded for managers with the assertion that „the most obvious managerial implication of the research reported here is that country risk measures are actually poor indicators of significant risk." This, however, did not impede the continued development of models and research by prominent scholars like Bouchet et al. and others, nor did it halt institutional risk assessments.

Academic models developed by scholars consistently compete with commercial assessment services, including those offered by the PSI Group, the BERI index service, and other specialized firms like Fitch Solutions GeoQuant, which utilize proprietary algorithms for country risk. GeoQuant's (2024) methodology aligns with several country risk services, such as CountryRisk.io, Coface, and Maplecroft, which all provide country risk assessments for a fee. The future of country risk modeling appears to be rooted in the high degree of certainty found within the models of these services and their ongoing research. The databanks created by these companies are most likely unparalleled by any academic research institution. Nevertheless, research within academia for new country risk models is still in progress.

A key question arises regarding whether new political or country risk models should adopt a vertical evaluation approach or a horizontal one, similar to the mathematical programming model proposed by Cosset et al., which employs methods compatible with statistical software such as R-Studio that can recreate and further develop models. Another foundational paper by Cosset et al. (1992) explored a decision support approach for evaluating country risk. Cosset defined country risk as „the probability that a country will fail to generate enough foreign exchange to service its foreign currency loans." He noted that checklist methods are the most commonly used evaluation techniques among bankers, while few are utilizing statistical models. Cosset introduced a decision support system for multicriteria analysis known as MINORA (Multicriteria Interactive Ordinal Regression Analysis), which allows for timely updates and quick detection of changes in the statistical relationships of model variables. To support his definition of country risk, Cosset stated that „a country evaluation system should incorporate leading indicators of potential debt servicing difficulties." For his country risk assessment, Cosset identified eight variables: 1. Gross National Product 2. Propensity to Invest 3. Net Foreign Debt to Exports 4. Reserves to Imports Ratio 5. Current Account Balance on GNP 6. Export Growth Rate 7. Export Variability 8. Political Instability. The regression analysis yielded significant results for the authors and advocated for the use of regression methods in country risk assessment. The illustrated methods allowed experts to modify the outcomes of the regression analysis. Since the model produced a ranking list of countries based on the regression analysis values, an expert could adjust the ranking if they believed a country was inaccurately assessed. This basic method indicated the potential for incorporating expert opinion even within data-driven models.

Furthermore, the evaluation of scenarios using Monte Carlo simulations, which have advanced the domain of game theory, is now being considered for country risk assessment. T. Bigler and A. Parthasarathy (1987) advocate for the use of Monte Carlo simulations in their paper, „Country Risk Assessment in International Lending," asserting that the systematic risk associated with global loan portfolios may exceed banks' expectations. The objective of a

Monte Carlo simulation is to advocate for the diversification of a multinational corporation's global business activities. This raises the question of whether models should focus on calculating risk, with risk mitigation achieved by reduction methods rather than diversity. E. Clark and R. Tunaru (2008) demonstrate an additional application of Monte Carlo in „The Evolution of International Political Risk 1956-2001," which exemplifies how Monte Carlo simulation can be utilized to forecast the probability of political occurrences.

In their 2003 publication „Country Risk Assessment: A Guide to Global Investment Strategy," Bouchet et al. et al. analyze the contributions of Robock, Desta, Miller, and Meldrum to provide an overview of nation risk assessment models. The summary illustrates that many risks are still included in more contemporary models, such as socio-political risk, economic risk, and natural risk. Ephraim Clark (2018), in his paper „Terminology and History of Country Risk," discusses cultural disparities in institutions, legal and financial traditions, and information sources. He also addresses significant constraints, including legal barriers, transaction costs, and discriminatory taxation, which can affect the outcomes of cross-border financial operations related to risk assessment.

Country Risk Analysis has furthermore introduced OSINT-driven models into the literature. Caldara and Iacoviello (2018) developed a monthly geopolitical risk (GPR) indicator by utilizing this type of data input. They constructed their GPR index in three steps: definition, measurement, and audit. Geopolitical risk is defined as „the risk associated with wars, terrorist acts, and tensions between states that affect the normal and peaceful course of international relations." For measurement, the authors created a monthly index that tracks the occurrences of geopolitical events as reported in leading English newspapers since 1985, along with a historical index that dates back to 1900. „The index reflects, in each month, the number of articles discussing rising geopolitical risks divided by the total number of published articles [...] The index is normalized to an average value of 100." The audit of the created database was conducted through „human reading" to ensure that the data was indeed GPR data. The main finding was the impact of GPR on nine variables. Their results were promising, leading them to conclude that their „index can be used to isolate risks—such as risks of war and terrorist attacks." Furthermore, „A detailed audit and a comparison with existing proxies confirm the GPR index accurately captures the timing and the intensity of heightened geopolitical risk." Their research illustrates the importance of OSINT data collection and timely analysis.

The 2012 Catalogue of Indices from the IPI (International Peace Institute) Global Observatory (2012) classifies indices into six groups: Conflict, Fragility and Instability, Environment, Freedoms and Rights, Gender, Governance, and Socio-Economics. The IPI catalogue focuses on various aspects of societal instability risk, which can be exacerbated today through the rapid dissemination of information via social media tools on a global scale. Many Western companies have had to learn difficult lessons recently. However, the IPI catalogue is highly specialized and should not be relied upon for comprehensive country assessments.

The Failed State Index, developed by the Fund for Peace (since 2005), utilizes the Conflict Assessment System Tool (CAST) based on Boolean logic. Similar to the IPI catalogue, the Fund for Peace's Failed State Index serves as a single-use tool that provides only a preliminary impression of a country's vulnerability.

Another author who should be mentioned here is Theodore Moran (1998, 2001, 2003, 2005), who published extensively in the field of political risk and was employed by the Multilateral Investment Guarantee Agency (MIGA) of the World Bank. MIGA plays an important role in the field of political risk insurance (PRI), and its research into political risk is significant. MIGA (2011, 2012, 2013, 2024) itself has published important studies on political and country risk.

Country risk assessment is crucial for insurance corporations, particularly when insuring international projects. Political insurance has a major role in ensuring the financing of projects subjected to any country risk (Gordon, 2008). Political risk insurance primarily covers three risks: expropriation, currency inconvertibility, and political violence. Certain political risks, like devaluation risk and inflation, are not covered by insurance. State agencies increasingly offer political risk insurance alongside commercial services, such as the Nippon Export and Investment Insurance Agency (NEXI), USA's Overseas Private Investment Corporation (OPIC), the World Bank's Multilateral Investment Guarantee Agency (MIGA), the African Trade Insurance Agency, the Inter-American Development Bank, and the Asian Development Bank. Prominent private insurance firms include Arthur J. Gallagher and Co. and AIG. These agencies can provide some insight to country risk researchers too, having also made contributions to the field by publishing on the topic of country risk assessment. However, their data and models are strongly protected proprietary information. Coface publishes the „Coface country and sector risk handbook," which gives managers an overview of the country risk Coface considered present and important (Coface, 2025). Additionally, the OECD (2025) publishes the „Country Risk Classifications of Participants in the Arrangement on Officially Supported Export Credits," which is also relevant for country risk managers.

The probability of an event that dictates the policy for payout can also be accurately predicted by state agencies due to their superior knowledge base. OPIC, for instance, obtains intelligence from the State Department. Utilizing public insurance such as OPIC can serve as a risk mitigation strategy, as OPIC fosters advantageous connections and ties in developing nations. This process is attributable, among other aspects, to the social and environmental requirements mandated by OPIC to ensure a project's viability. In addition to the policies provided by OPIC, every investor should participate with host governance wherever feasible, since it presents an advantage in risk mitigation (Waters, 2015). Determine the total size of the global PRI. Corporate diplomacy is an emerging domain for this objective as well.

The development of new methods to assess country risk is ongoing in this research field. While expert opinions were heavily sought when the implications of country risk became apparent to the management of multinational corporations, the models evolved, incorporating increasingly sophisticated mathematical methods for evaluation. This evolution included a significant focus on regression analysis, which became a dominant approach in economics. Other mathematical techniques were also employed. However, a new opportunity has emerged for country risk assessment through machine learning and artificial intelligence. Although a large language model can provide insights into a manager's risk concerning the current situation in any given country, this approach represents only a basic application of artificial intelligence for country risk assessment. Researchers have also developed more advanced applications for this purpose, including the use of neural networks. The computational power now accessible to many researchers enables the creation of more complex models. Further research and methodological advancements are clearly necessary to enhance country risk assessment using artificial intelligence.

2.1 The many aspects of country risk

Country and political risk can now look back on a long research history. These fields have repeatedly been represented by state-of-the-art techniques compiled in research papers, which provide an outlook on their future direction, as seen in works like Robock (1971), Coplin (1983), Ghadar et al. (1983), Wafol (1998), Chermak (1992), Lindeberg and Mörndal (2002), Bouchet et al. (2003), Michael and Gerald (2005), Baas (2010), Hammer et al. (2011), Wagner (2012), Sottilotta (2013), Menocal (2013), Toksöz (2014), Costa and Figueira (2017), Girard (2018), Hetou (2019), Bouchet et al. (2018), Gaillard (2020), Klement (2021), Sun et al. (2021), and Llada (2022). Impressive as the work of scholars is, country risk always adds aspects to its complexity, and new techniques are added to assess these risks.

One of the areas where country risk assessment is crucial is in evaluating the risk of government bond defaults. The trading of government bonds, especially in the secondary market, is heavily influenced by investors' confidence in the government's ability to repay its debt. Various factors shape the perception of a government as solvent and, therefore, stable. While sovereign risk alone does not encompass the full range of country risk factors, it remains a significant consideration. Additionally, all aspects of sovereign risk can be incorporated into a country risk model if needed. Financial multinational corporations can also be direct bondholders of a country, which entails the highest level of exposure to sovereign risk default. Structural models addressing this issue were established by Eaton et al. (1986). Although credit rating models originated in academia, they are primarily utilized and continuously refined by institutions such as Moody's, Standard & Poor's, and Fitch. A significant amount of refined data concerning country risk is maintained by rating agencies. The ratings produced by agencies such as Moody's and S&P remain crucial for countries and multinational corporations, despite the decline in their reputations following the financial crisis.[1] Nevertheless, the methodologies used by these agencies to assess sovereign risk date back to the early 20th century, and the significance of their ratings has not diminished. These ratings continue to influence premiums for various loans and financial products, and they can impact the macroeconomic policies of countries (Kaminsky and Schmukler, 2002).

Additionally, magazines like Euromoney and Institutional Investor have also been instrumental in the field of country risk research, publishing their sovereign risk ratings. The ratings from both the magazines and the agencies have increasingly adopted quantitative methods. Gaillard (2020) criticized this trend, stating, „The main problem is that rating analysts are now ensnared in quantitative risk assessments that allow little room to maneuver when adjusting ratings upward or downward. Furthermore, the quantitative criteria do not always permit one to anticipate debt crises. The reasons are that (a) most such indicators (e.g., the WEF Global Competitiveness Index and the unemployment rate) assess a country's structural strengths and

[1] The financial crisis refers to the 2008 housing market collapse, which led to the failure of Lehman Brothers and triggered a severe crisis within the global banking sector.

weaknesses and (b) most ratios are stated relative to GNP or GDP (e.g., current account balance to GNP, public debt to GDP) and so are therefore insufficiently sensitive to current events.” He argues that the disproportionate emphasis on the ratio of general government debt to GDP fails to distinguish between developed and developing countries, despite their differing abilities to manage debt. According to him, „Hence it is fruitless to classify countries on a risk scale that is based on this ratio, as Moody’s currently does.”

The variables of all these models however, are the key to country risk assessment and a representation of the variety of risks and specialization within the different models. GDP and other economic variables are most common for evaluating credit default risk, while the number of major security incidents is a variable for political instability assessment. The multitude of factors influencing country risk complicates the integration of all necessary variables for country risk models. Kennedy (1987) described the expert-generated models and methodologies that were consulted by the banks, including the risk assessment of government bonds: the Business Environment Risk Index (BERI), the Business Intelligence (BI) system, and Nikkei's Business Index (NBI). BERI is recognized in Kennedy's book with 15 variables listed in Table 1: political stability, foreign investment attitude, nationalization, monetary inflation, balance of payments, bureaucratic delays, economic growth, currency convertibility, contract enforceability, labor cost/productivity, professional support, communication/transportation, local management, short-term credit, and long-term capital.

The Political, Security and Socioeconomic Instability Index (PSSI) indices and operational variables include a socioeconomic index, which was initially overlooked in country risk assessments. However, later models acknowledged the importance of social factors as significant risk elements for multinational corporations, even in analyses focused solely on government debt risk. The PSSI indices consist of the following components: The PSSI model recognizes the impact that civil unrest and negative social developments can have on government, politics, and economics.

The International Country Risk Guide (ICRG) model was developed in the 1980s and was later incorporated into the PRS Group. While many aspects of the team behind the ranking remain unclear, Professor Howard Howell appears to have been significantly involved in the project and continues to publish articles for the PRS Group related to country risk. Howell (2001a) published, for example, the „International Country Risk Guide (ICRG) methodology: Background of the ICRG rating system.” The ICRG model employs 22 variables across three categories of risk: political, financial, and economic. The political category is assigned an index of 100, while the financial and economic categories each have an index of 50. The scores that a country achieves within each category are updated on a monthly basis (Gilliard 2020). The PRS Group holds a prominent position among specialized consulting firms that focus on country risk.

PRS Group ICRG Rating System	Political	Financial	Economic
	Government stability	The ratios of foreign debt to GDP	GDP per capita
	Socioeconomic conditions	Foreign debt service to Exports of goods and services	Real GDP growth
	Investment profile	Current account to exports of goods and services	Annual inflation rate
	Internal conflict	The net international liquidity position	Budget Balance as a Percentage of GDP
	External conflict	The country's exchange rate stability	Current Account Balance as a Percentage of GDP
	Corruption		
	Military in politics		
	Religious tensions		
	Ethnic tensions		
	Law and order		
	Democratic Accountability		
	Bureaucracy quality		

Figure 2. ICRG Country Risk Rating System by the PRS Group Illustration by author based on Howell (2001a)

Supranational bodies like the United Nations Conference on Trade and Development (UNCTAD) have developed specialized knowledge in evaluating the dynamics of foreign direct investments, including both inward and outward flows. They also offer details about the operations of multinational corporations across various host countries. According to Bouchet et al., UNCTAD „also presents a range of variables related to the activities of foreign affiliates in the country and foreign affiliates of home-based TNCs“ (Bouchet et al. 2018).

2.2 The role of Banks in Country Risk Modeling

Banks have played a vital role in developing country risk models. U.S. banks were pioneers in creating the first civil-use models by employing checklist methods and expert analysis. Banks were sometimes even more entangled in country risk beyond their direct exposure to it. Sachs (1989), while examining the debt crisis of developing countries, warned about the effect that rapid increases in interest rates have on heavily indebted developing countries and about the irresponsible cross-country lending of commercial banks to LDCs at that time. Meanwhile, central banks and other supranational institutions have continued to establish frameworks for these models and have created widely used public databanks (Bank for International Settlements, 2025). They identified and selected specific aspects of country risk that posed threats to their investments, incorporating these factors into their model variables. For instance, American Express evaluates several key factors, including reliance on foreign capital, dependence on imports, revenue vulnerability, debt repayment obligations, monetary and fiscal regulation, openness to private and foreign investment, the relative significance of a nation, and political risk.

The introduction of country risk models in the commercial sector faced significant challenges, as noted by Gaillard (2020). In the 1970s, approximately forty banks, according to the Exim Bank, implemented some form of country risk assessment. However, the majority of these banks did not back-test their models for accuracy and were primarily focused on determining exposure limits related to country risk in their investments. Smaller banks relied on country risk assessments produced by major financial institutions, such as the World Bank, the International Monetary Fund (IMF), and Exim Bank. The national banks that advanced the development of these models employed „dissimilar country risk assessments" when outlining their methodology for evaluating country risk. They started with „simple checklist methods" and progressed to their first „sophisticated models" in country risk assessment. Gaillard (2020) outlined the solution in his book: „In 1978, the three federal bank regulatory agencies (the Office of the Comptroller of the Currency, the Federal Reserve Board, and the Federal Deposit Insurance Corporation) adopted a uniform examination procedure for evaluating country risk factors in international lending by US banks." Additionally, this procedure limited the concentration of exposure to any single country (Federal Reserve Bank of New York, 1978, as cited in Gaillard, 2020). The system involved „identifying countries with actual or potential debt-servicing problems, bringing loans to these countries to the attention of bank management in examination reports, and assessing banks' internal country exposure management systems"

(General Accounting Office, 1982, as cited in Gaillard, 2020). Nonetheless, banks continued to refine their assessments and further research in the field of country risk assessments. Shapiro (1985) therefore looked at the „currency risk and country risk in international banking."

Mellon Bank's Country Evaluation System concentrated on various categories. In terms of liquidity, it analyzed reserves relative to imports, debt service in relation to exports, significant reserve deficits, delayed payment histories, and IMF credit compared to quotas. The structural analysis examined changes in consumer prices, money supply, and real GNP, as well as variations in domestic credit, the monetary base, and purchasing power parity. Additionally, it considered the growth of a country's exports relative to global export growth, the percentage of GDP dedicated to goods and services exports, total debt in relation to these exports, along with gross domestic product savings and real per capita growth.

At Bank of America, judgmental indicators included economic indicators that evaluated the effectiveness of monetary policy and economic policies in various countries. This analysis covered financial regulatory frameworks, government attitudes toward investment, management quality, access to global credit, and currency valuation. Political indicators assessed the effectiveness of government policy formulation, the capacity for conflict resolution within institutions, orderly governmental succession, the extent of checks and balances among institutions, the potential for social unrest, external security threats, relations with the United States, and relevant regional alliances (Kennedy, 1987).

Country risk classification is not exclusive to private banks; central banks, public development banks, and other government-controlled financial institutions also engage in this process. Their assessments and models are often utilized or integrated with the models developed by private banks. Ratings from government-controlled entities, both national and transnational, remain vital to country risk modeling. According to Bouchet et al. (2018), „Monitoring international bank exposure is a key component of country risk analysis, not only for close tracking of the confidence or nervousness of international banks in a particular country, but also for assessing the likelihood and extent of contagion effects." This monitoring includes the central banks of OECD countries and should, ideally, extend to every national central bank that produces valid economic reports.

The ranked perceptions of country risk variables, as reported by bank respondents, encompass the current account balance, trade balance, balance of payments, GNP growth rate, export diversity and stability, export market concentration, inflation, foreign exchange controls, foreign exchange rate, money supply growth rate, savings as a percentage of GNP, GNP per capita, investment as a percentage of GNP, foreign investment climate, terms of trade, labor force profile, and interest rates. The EXIM (U.S. Export-Import Bank) employs a credit classification system (CC), ranging from 0 = exceptional good credit quality to CC1, CC2, CC3, CC4, and CC5 = weak credit quality (Bouchet et al., 2003). However, Gaillard (2020) criticized the EXM Banks ratings and therefore model in his research harshly: „Nonetheless, the Exim Bank's risk assessment policy was extremely lax. In several annual reports, the bank stated that „because of the unpredictable nature of future economic and political conditions throughout the world, the risk of loss on Exim Bank's loans, guarantees, and insurance [was] not susceptible to accurate measurement" (Exim Bank, 1969, as cited in Gaillard, 2020). It is therefore not surprising that the share of outstanding loans classified as delinquent or rescheduled increased inexorably in the 1970s and exceeded 10% in 1981 (General Accounting Office, 1982, as cited in Gaillard, 2020). The 1982 debt crisis undermined the Exim Bank's credibility and expedited its decline."

Variables such as GDP, balance of payments, and national debt levels remain among the primary factors considered when constructing a country risk model. However, MNCs face challenges because banks typically publish country risk models that are either retrospective or not tailored to the specific business interests of a country. Furthermore, banks fail to reveal their internal data sources or offer comprehensive explanations for their assessments. While banks contribute significantly to the field of country risk, their focus is often limited to lending aspects, which may not be sufficiently broad or relevant for MNCs. MNCs would derive the greatest benefit by using these variables as a foundation for developing their own models.

In 2021, the IMF published a report titled „How to Assess Country Risk: The Vulnerability Exercise Approach Using Machine Learning," which details their methods for evaluating country risk. The IMF's Vulnerability Exercise introduced the assessment of their models as follows: „The models assess the near-term risk of a crisis in the external, financial, fiscal, and real sectors. In each sector, rigorous performance metrics are used to compare new tools against traditional approaches. It turns out that random forest-based models, which are popular modern machine learning (ML) methods that average over many decision trees, outperform other options in most cases. In other cases, the signal extraction approach, a robust non-parametric method designed for macro-crisis detection, performs best. These winning models represent a new generation of models at the core of the VE."

The report further praises machine learning tools, stating, „Machine-learning tools are well-suited to the challenges of macroeconomic risk assessments [...] Without sophisticated designs, classical estimation methods, like logistic regressions, may be poorly suited to capture the interactions, nonlinearities, and high degree of cross-country heterogeneity in crisis assessment. ML tools have become increasingly popular to address these issues in economics and other fields and have shown promise specifically in the case of crisis prediction."

The IMF continually tests their models against each other and introduces the best-performing ones. They found that due to the non-linearity of country risk, „a useful model should be able to efficiently sift through a broad range of potential independent variables, identifying the relationships, thresholds, and interactions that are most informative when making a prediction. Complex ML algorithms [...] are designed to explore the dataset more completely, finding key predictive relationships and interactions."

However, the report views neural networks as a method that has yet to demonstrate its advantages. In contrast, it notes that tree-based models are favored by the IMF: „Tree-based models are the most successful in out-of-sample prediction for the financial and fiscal sectors [...] One key feature of tree-based models is their ability to identify interactions between any pair (or higher-order tuples) of variables. Such interactions cannot be captured by signal extraction models, and including all possible interaction terms would cause the loss of stability and robustness in traditional econometric models."

This report highlights that the models are estimated on thousands of examples, which is too many to sort through individually to identify useful guides. Fortunately, „similarity scores" identify current and past country cases that are the most similar to the country in question, based on the number of instances when the regression forecast model places two countries in the same final „node" of the tree. The IMF states that „the contribution of each explanatory variable can be captured by Shapley values." The variables are utilized in the IMF's ML models within the External Sector Model, the Fiscal Sector Model, the Financial Sector Model, and the Real Sector Model. All models present conclusive and valuable results, with many being back tested for decades.

While private banks have played a significant role in developing country risk models, the IMF is currently advancing public institution models based on state-of-the-art machine learning techniques. Although the IMF is a multinational organization rather than a traditional private or central bank, it serves as a representative of the ongoing development of country risk assessment by banks and other financial institutions. As long as the financial system remains stable, banks will continue to play a crucial role in assessing country risk and developing innovative models for this purpose. The report fittingly concludes with the statement, „Machine-learning techniques offer new opportunities in risk assessment. Beyond the crisis risk assessment models presented here is a wide horizon of techniques that economists are only beginning to apply to risk assessment. Multi-classification models, which can simultaneously assess the possibility of different combinations of crises, offer a clearer understanding of how the crises studied here overlap or contribute to each other. There is also room to move into bigger data, higher frequency series, and less structured information for a short-horizon crisis risk assessment, leveraging more advanced ML techniques."

2.3 Risks

Robock (1971) and Kobrin (1979) pointed out that political risks can also have positive effects on a business operation and don't have to be consequently impacting it negatively. The positive effects of political risk on business operations are examined while developing strategies to profit from it (Beardshaw et al., 2012). Zaremba (2018) however, found in his attempted of developing strategies that the risk-based strategies are not robust. Furthermore, the development of mitigating strategies against country risk is expanding likewise, with theories of portfolio diversification, for example Damodaran (2003). However, within this thesis, only the negative effects of risk on an MNC will be examined.

Country risk models mainly split the risks of MNCs into two main categories: micro risk and macro risk. The latter distinction partially due to the work of Robock (1971), who introduced this separation of risk. Later on, confirmed and amplified by other scholars like Alon and Herbert (2009). While micro risk affects the company as an individual entity and is bound to the direct industry environment of the company, macro risks are secondary, sustained by an MNC from developments in an overall industry or country. Bouchet et al. (2003) divides the authors into two groups regarding macro risks. For the first, „country risk narrowly originates from adverse governmental or sovereign actions;" the second group „refers to the environmental instability and its impact on business conditions."

Bouchet et al. (2018) declared again that „Risk, Uncertainty, and Volatility" are much too complex to get completely represented in a mathematical model. „Regarding country risk management, globalization increases uncertainty due to the integration of a complex economic and financial system that breeds volatility, contagion, and crisis contamination." The current global situation is supporting his positions in terms of the complexity.

The micro economic aspects are not minder complex. Reaching from new cybersecurity concerns to targeted hostilities because of the company's industry sector. Threaten by ESG litigation, the retraction of political favoritism in host countries or other sustainable risks. The micro environment for MNCs become even more complex in every host country around the world. Global value chains a topic of macroeconomic risk, can become a micro risk due to activist political groups, which is targeting a single MNC operating along the value chain to the misliking of these groups.

2.3.1 Micro

When corporations establish microeconomic conditions through their operations in a foreign nation while being influenced by the macroeconomic environment, it is essential to understand the how, why, and when of these interactions. The risks associated with these circumstances are similar to the previously mentioned concerns: political, economic, and sociological. The PESTEL framework has been a crucial model for evaluating corporate environments in the past, encompassing political, economic, social, technological, ecological, and legal factors. All of these reasons, including technical considerations, are significant contemporary factors for assessing micro risk aspects of country risk too.

Robock (1971) examined micro risks from a purely political perspective and deemed them more prevalent than macro risks. He noted that micropolitical risk, defined as the risk of government intervention in a specific multinational corporation's foreign business operations, was particularly high in industries such as public utilities, petroleum, and finance. He stated, „Some industries can begin with political favoritism and later be subject to unfavorable political environments." This is in direct contrast with macro risk, where negative developments are not sector specific but economy-wide.

Management can see the manifestation of micro risk most clearly in the evaluation of specific completed projects rather than in the quarterly determination of general business operations. While a decline in business can have many reasons, a project failure can be examined. If a project encounters sudden problems with its financing, the company can observe the altered risk evaluations from banks, which may stem from either micro or macro factors. In private-public partnerships, the behavior of the government partner clearly indicates that risks were not identified. If projects are connected to sector-specific investments, the management can determine the micro risk it was subjected to.

A micro risk emerging in today’s landscape is the threat of cyberattacks specifically targeting certain companies for economic or political espionage. The frequency of these incidents is increasing, leading to a burgeoning market for cybersecurity solutions. Assessing the prevalence of cyberattacks in a particular country can be challenging, but managers should evaluate whether a specific project or location in a host country heightens the risk of becoming a target. This evaluation should also encompass considerations of data sovereignty and network security.

Data sovereignty mandates that sensitive data be stored on company-owned servers or, at the very least, with trusted third parties. Storing data on local external servers may result in breaches of confidentiality. A pertinent example is China, where intelligence laws compel companies to comply with requests from the government. Consequently, data held by a Chinese partner company must be surrendered to Chinese authorities when requested. Yuan and Ji (2019) researched political risk from the point of view of Chinese firms and found that they are risk-averse. In developed countries, they face headwinds because they are considered a security threat. The above-mentioned security laws are most likely a manifestation of these concerns in developed countries. Goswami and Panthamit (2022) conclude that political risk -particularly negative perceptions of China among partner countries- is a major deterrent for nations seeking to increase their trade relations with China.

Furthermore, network security poses an additional local risk, particularly due to the critical need for a reliable internet connection. In certain countries, networks can be compromised, resulting in potential data theft.

Community opposition can be a substantial risk factor for countries that are experiencing political instability; but it can also be highly specialized to particular industry sectors, regions, or even individual multinational corporations. As an illustration of these micro-manifested hazards, consider the demonstrations that indigenous peoples staged in response to land demands.

A similar manifestation of corruption can take place on a micro level, which takes place when local governments or authorities in control of particular sectors engage in bribes in order to smooth operations. An excellent illustration of this may be seen in the oil exploration industries of developing countries, which may operate in a manner that is distinct from that of other industries occurring within those countries.

Due to the fact that problems associated with regional governance frequently originate from larger federal difficulties that are representative of macro-level trends, determining whether these problems are macro or micro hazards can be a difficult and complicated process.

The world of sociological elements that are influenced by globalization is another sector that is undergoing rapid change. This realm includes the rapid spread of news and the emergence of social media. Over the course of time, campaigns of outrage have been successful in swaying public opinion in a number of Western countries, particularly with regard to issues concerning society and the environment. Additionally, adversarial societies, especially in industrialized nations, have been impacted by these elements of globalization. Companies have been compelled to concede that they are unable to conceal corporate misbehavior in developing countries as a result of increased access to news and the ability to protest. The qualitative monitoring of this risk should be the primary method of risk management, and the quantitative analysis of the data gained from it should serve as a secondary measure.

Sector-specific (micro) country risks are so extensive that country risk models must address them in a manner tailored to the specific industries in which multinational corporations operate, such as infrastructure, finance, energy, or agriculture. MNCs cannot simply overlook these risks, as they consider themselves to be beneficial to both the host country and the local communities (Alon and Herbert, 2009). In addition to Alon and Herbert (2009), Al Khattab et al. (2007) also investigated managerial perceptions of political risks and were referenced by Alon and Herbert. However, the model proposed by Alon and Herbert more effectively captures the complexity of micro-country risks and their overlap with broader country risks, providing a foundation for further research.

Adverse changes and enforcement of regulation by host governments are a micro country risk as well, including, for example, employment regulations. For Alon and Herbert (2009), the risks can be divided into internal and external risks. International risks are economic-related factors: labor conditions (chance of unionization, etc.), congruence with national economic interests and goals (national priority arguments for the particular business sector, etc.), and availability of alternative suppliers. Society-related factors: Power distance (in hierarchical societies, the society is further away from the governing force), uncertainty avoidance (the unwillingness to avoid foreign ideas and distance from established codes and practices, etc.), and collectivism (in countries dominated by collectivism, the favoritism of the group interest is often difficult to penetrate for MNCs home-based in individual countries). Government-related factors: Nationalism, level of governmental control, congruence with governmental goals („Firms whose practices are at odds with the policies or priorities of the host country's government tread on thin ice"), transparency, and corruption.

Elements of the external dimension for Alon and Herbert are: Economic-related factor: Degree of economic dependence („The more dependent the host country, the lower the level of political risk facing home country firms"). Alon and Herbert, however, rightfully mentioned that the exploitation of the status quo can lead to political risk, home country economic policies (the risk of retaliation against home countries' adverse policies towards the host country), and balance of payments („Deficits in BOP often need to be remedied through trade or currency controls, particularly on the MNC's home country"). Society-related factors: Home country or third-party public opinion, international activists (engaging in negative actions for the MNC, etc.), degree of cultural distance („The extent to which the firm and the host country are culturally dissimilar affects political risk"). Government-related factors: Diplomatic or economic relations, membership in bilateral and multilateral agreements, and currency (in)stability. Elements of the firm-related dimension: contribution of the firm to the local economy, size of operations, level of exports, bargaining power of the firm relative to the local government, dependence on the local market, extent of natural resource seeking, and level of firm diversification („A firm with only one host country or one product, for internal consumption or for export, is much more vulnerable to micro political pressures"). Governance structure: Extent of local ownership, financial policies adverse to balance of payments, intra-corporate transfers („These transfers are indicative of how much the affiliate and parent firm are integrated") (Alon and Herbert, 2009).

Alon and Herbert’s (2009) model encompasses both micro and macro country risk aspects, with implications for micro risks. Notably, host countries may limit their retaliation policies to specific industries or business sectors. Multinational firms must thus constantly assess whether their industry is a more important target for government reprisals. The model developed from these variables serves as a classical qualitative evaluation tool. It consists of six columns: column 1 lists the variables; column 2 assigns a factor of importance; column 3 describes the factor's impact on the firm; column 4 indicates its occurrence; column 5 calculates the product of columns 3 and 4; and column 6 computes the product of columns 2 and 5.

While the qualitative assessment model is part of the ongoing discussion regarding whether qualitative or quantitative models are better suited for country risk assessment, the emphasis on and evaluation of micro risks are understandably highlighted for their significance. Country risk scholars should consider how these micro risks are incorporated into their models (Alon and Herbert, 2009).

Another potential source of micro risk is the local workforce in the host country. It is common knowledge that certain nations engage in economic espionage against foreign businesses and use local employees in order to acquire access to confidential information. MNCs are aware of the issue, but they are unable to adequately interact with it all the time. On top of that, Robock (1971) had previously seen an issue with the job situation in the area in the 1970s. Robock brought attention to a problem that is still pertinent today in relation to multinational corporations and their investments in China. He stated, „Over the course of time, countries are able to accumulate capital and nationals who have learned the techniques of the foreign enterprise.” To the extent that local individuals have been trained for copper mining, running a tea plantation, or managing any other form of business that was launched by foreign corporations, there is a likelihood that the political pressure to restrict or eliminate foreign enterprises would increase.

In sectors such as firm security, logistics, and transportation, multinational corporations frequently collaborated with local entities that were not trusted. Should breakdowns occur in these sensitive areas, it is possible that considerable losses would be incurred in terms of both investments and business property.

New bribery compliance legislation, such as the Foreign Corrupt Practices Act (FCPA) and the United Kingdom Bribery Act (UKBA), pose a threat of enforcement for multinational corporations (MNCs) that engage in bribery of local officials in developing nations. These countries are working to improve their image of lawfulness in the international community. The delays in obtaining permits and the initial challenges in securing licenses for specific business operations pose risks for multinational corporations, particularly when these licenses were previously acquired in ambiguous areas of the local legal framework.

In addition to macro risk, it is necessary to take into consideration the exposure to political risk at the micro level. where it comes to assessing these risks, qualitative analysis through the use of expert opinion can be an extremely useful tool, particularly in this day and age where risk is frequently evaluated quantitively. Experts are able to evaluate the dangers that a multinational business is exposed to by utilizing the specialized information networks that they have established within the host nation. In addition, there are situations in which experts may be engaged for outreach campaigns that are directed toward communities and other potentially antagonistic entities.

It is essential for a corporation to conduct thorough research on the micro country risk encountered in a host nation, and this research must to be clearly mapped out for management. MNCs should make every effort to reduce risk whenever it is viable to do so by utilizing risk mitigation tools such as risk insurance or community participation. CSR and ESG strategies, which stand for corporate social responsibility and environmental, social, and governance, respectively, should not only serve as marketing tools; rather, they should involve actual efforts to develop links within the communities of the host country. In this aspect, a great number of businesses continue to fall short.

Furthermore, it is important to note that micro- and macro-country risks can overlap, complicating model design. This distinction is still useful, though, when defining variables and data gathering techniques for country risk models. Alon and Herbert (2009) emphasized the commonalities shared by micro- and macro-political risks (Figure 3). Although their illustration does not encompass all macro- and micro-risks and uses a less refined categorization, it remains plausible.

There is little doubt that in high-complexity host-country situations, efficient risk management of micro-country risks is absolutely necessary. While the aspects of micro-country risk are extensive, so too are the potential reactions of CEOs and managers to political risk. Even if a model has previously provided an accurate analysis of micro risks to the firm, the decision to act on the model's results ultimately depends on the manager's evaluation and judgment (Giambona et al., 2017). However, models should not be developed with the manager's perspective as the primary focus; instead, they should strive for the most accurate assessment possible. The goal of the model is to generate optimal outcomes, not to influence the manager's decisions. Additionally, another risk associated with micro-country risk is the potential damage to the reputation of the multinational corporation or the deterioration of relationships with stakeholders, which may result from efforts to engage with and mitigate political risk. Nonetheless, the model should only consider these factors after thoroughly assessing the associated risks.

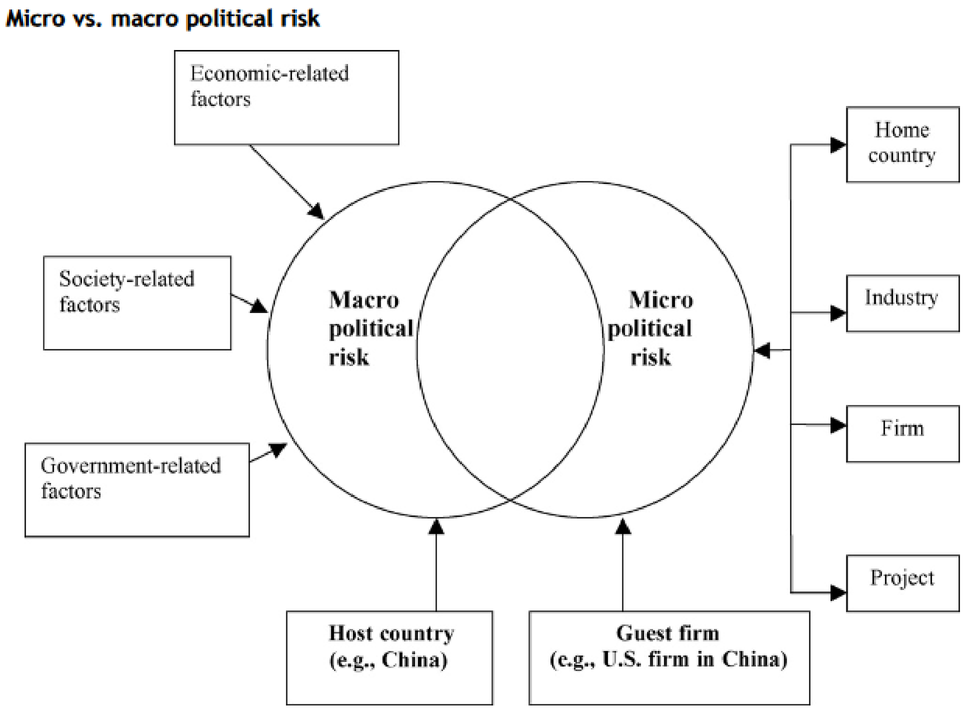

Figure 3. Micro and macro political risk according to Alon and Herbert (2009)

2.3.2 Macro

MNC activities are subject to macroeconomic risks inside the host nation, which can have an impact on the host country's capacity to serve as a site for manufacturing facilities as well as its function as an export market for the MNC's products. Macroeconomic instability has an effect on economic considerations and can inspire government action, both of which have a negative impact on multinational corporations based in other countries. Kobrin (1979) describes macro country risk in terms of „the risks associated with the political environment of a host country that affect all foreign enterprises in a similar fashion, regardless of industry or specific firm characteristics." In addition, this term may include legal, social, economic, and environmental variables that are influenced by political processes. There has been a recent increase in the environmental risks that are related with macro national risk, and it is anticipated that this trend will continue. For multinational corporations operating in host countries, hostile legislation that interferes with commercial operations may become a reality. For scholars examining macro country risk from a historical perspective, the documented negotiations for a New International Economic Order (NIEO) conducted by the Group of 77 serve as a valuable archive. One objective of the G-77 countries was to gain greater control over transnational businesses, specifically multinational corporations, as they perceived these entities to be detrimental to their national economic interests (Bhagwati, 1977).

According to the discussion in, it is anticipated that political and social threats will continue to dominate this century. This is due to the fact that problems of inequality and resource shortages may lead to new conflicts on a global scale. Multinational corporations are not the only ones that are impacted by the amount of macro country risks; global finance and international trade are also impacted by these risks. When macro national risk is taken into account in both economic and political contexts, it has a substantial impact on the functioning of markets and the interactions between corporate entities. It is possible that capital flows, such as foreign direct investment, would decrease, which might make it difficult for countries to achieve economic growth. Additionally, the political capital that a multinational corporation owns in a host country may also decrease.

Macroeconomic risks, on the other hand, do not necessarily have to be concentrated on multinational corporations or the particular industry in which they operate. This is in contrast to microeconomic risks, which are centered on individual industries. It is possible for macro risks to cross national borders in today's globalized world, meaning that they can have an impact on numerous countries or even manifest themselves on a global scale. Numerous nation risk models provide a clear illustration of the significance of macroeconomic risk in the arena of country risk. These risks rank among the most often utilized variables in both quantitative and qualitative evaluations, demonstrating that they are among the most important factors to consider. Gross Domestic Product (GDP), which acts as a chronology that reflects the economic trajectory of a country, is one of the most important indicators of macroeconomic risk. It is also one of the most important indicators available. The inflation rate, which is an indicator of the financial health of a nation, comes in a close second shortly after this. Tax deficits and rising levels of state debt can be uncovered by both the gross domestic product and inflation. Other variables that are frequently incorporated into these models are the trade balance, foreign resources, and direct investments from overseas organizations. It is possible that a reduction in any of these categories could result in a downgrading of the credit rating, which is typically connected with country ratings, as well as the possibility of sovereign default.

At a number of different levels, political instability can be observed. The early symptoms frequently consist of demonstrations, while the most severe outcome for a multinational corporation may be a coup d'état or a change in the established government of the country in which it operates. Today, those in charge of managing country risk are confronted with the difficulty of the rapid evolution of political instability within these countries. Through the use of social media, it is possible to enable the rapid dissemination of demonstrations and the organization of opposition groups. Despite the fact that the means of protest have changed as a result of the proliferation of social media, the fundamental factors that contribute to political instability have not altered. The persecution of political opposition, corruption, and inadequate governance are all issues that continue to present concerns all throughout the world, particularly in emerging countries. There has been a noteworthy shift in the number of countries that desire to exercise their influence, and these states that have been affected are once again becoming focal points for the geopolitical ambitions of great powers.

In addition to the dangers that arise from political instability through social developments, the unpredictability of government policies can also be a substantial risk factor when they are implemented in the absence of input from outside sources. Throughout history, host countries have displayed unfriendly policies toward foreign enterprises, and it is possible that same policies could reappear in the future. A hostility or retribution against sanctions imposed on the host country, as well as a worsening in international relations between the host country and the home country, are examples of actions that the government may do, and these actions are predictable. On the other hand, unexpected government expropriations or nationalizations offer hazards that are more difficult to forecast on account of the fact that governments may take these moves in order to earn political capital within their own borders. It is well knowledge that nationalistic feelings are on the rise in both established and emerging nations. This is for the simple reason that multinational corporations from other countries are frequently viewed as hostile entities that take advantage of local resources and harm indigenous firms.

More recently, the Spanish business Repsol, which suffered large losses as a result of the renationalization of Repsol YPF in 2012, is an example of a multinational corporation that was affected by macroeconomic risk. The year 1999 marked the beginning of Repsol YPF, which was founded after Repsol purchased a significant part in the corporation. This example exemplifies the severe steps that a government may adopt in response to economic pressures that influence the opinion of the general populace. Business operations that are conducted in other countries have the potential to become political targets, as the actions that are driven by profit could be considered intrusive during times of crisis.

As far as macroeconomic country risk variables are concerned, the majority of study has been conducted in terms of economic risk characteristics. Due to the fact that markets are highly responsive to economic policies, many national economies found themselves in a precarious position to take action as a result of currency instability and exchange restrictions. These economic strategies have the potential to also result in the political instability that was described earlier. Inflation and interest rate volatility are well-known results of poor or even completely irrational economic policies of host countries. These policies might lead to a complete economic catastrophe in a country, which is a consequence that deserves to be known. Models of rating agencies, etc., have nevertheless failed in the recent past to see the impact of poor economic policies, such as the economic crisis that the European Union experienced in the 2010s. This is despite the fact that macroeconomic data moves more slowly than data on political instability and is easier to obtain, even if it is not time sensitive.

Because of this, it is essential to evaluate the viability of debt and the possibility of a sovereign default, not only for multinational corporations that have financial interests in the country, but also for MNCs that are looking to evaluate the stability inside a nation. The development of the economy of a host country at a macro level can have a substantial impact on the micro level, such as a decline in purchasing power, or it can lead to unfavorable political implications for businesses. It is possible for economic mismanagement to give rise to populism, which highlights the connection between economic risks and political hazards when they manifest during times of economic instability.

A further sign of economic risk is the evaluation of the balance of payments, which multinational corporations should keep an eye on, particularly if it is impacted by a trade imbalance. A country is said to be experiencing a balance of payments crisis when it is unable to continue financing its sovereign debt. Again, the impact of sovereign debt on macroeconomic performance is linked to country risk (Sachs, 1989). There is a possibility that a trade deficit could be a contributing factor in the development of a balance of payments crisis, even though this circumstance does not always have a direct correlation with a trade deficit. Countries that have significant trade deficits frequently require financing from outside sources, which might give rise to a crisis of this nature. Recent efforts made by Donald Trump to address the trade deficit in the United States of America are a good illustration. The ranking of the dollar was decreased by rating organizations, and the government debt of the United States of America continues to increase. In spite of the fact that the United States of America continues to have a functional economy and is not now experiencing a balance of payments crisis, multinational corporations from Europe, Canada, Mexico, and China continue to face dangers since their distribution markets in the United States are in danger of declining.

At the same time as all macroeconomic risk is classified as country risk, it is essential to keep in mind that macro country risk comprises the components that have been described in the sections that have come before and after this one.

A considerable macro risk is posed by lax legal systems and difficulties in the execution of contracts in the country that is hosting the situation. Through the establishment of the World Trade Organization (WTO) and the General Agreement on Tariffs and Trade (GATT), the United States of America has made it a priority to provide assistance to its multinational businesses. The purpose was to protect the interests of both the United States of America and its multinational corporations that are active in other countries. Generally speaking, the stability of legal systems and the efficiency of enforcement are often worse in emerging countries compared to developed nations. During the time period following World War II, when democratic governments started to develop in countries that had previously been colonies, the difference between the rule of law and arbitrary governance became increasingly pronounced. In many countries around the world, efforts are still being made to develop legal systems that are both functional and uncorruptible.

When it comes to tax regulations, labor legislation, and finance requirements, multinational corporations are more likely to experience sudden legislative changes than other institutions. In the context of market openness, the development of trade barriers represents a classic example of a legal risk. Although the World Trade Organization and the General Agreement on Tariffs and Trade continue to hold legal authority, the legal environment concerning trade barriers for multinational corporations is undergoing change. There has been an increase in the number of bilateral trade agreements and new economic cooperation as a result of the establishment of a multipolar world. These developments are having an impact on the freedom of commerce for multinational corporations and their international competitors. Additionally, environmental regulations are becoming increasingly important in host nations as a result of the growing significance of environmental concerns in the process of assessing the risk of their respective countries.

The emergence of a single macroeconomic risk can also set off a chain reaction of contagion effects that can result in the occurrence of other sorts of crises. As an illustration, a crisis in the macroeconomic sector might initially lead to political instability, which can then lead to difficulties in obtaining external finance for multinational corporations. It is possible that a problem with the environment may force the government to take action, which may have unexpected repercussions such as the withdrawal of foreign direct investment funds. The rise of a new government can have a negative impact on a country's rating, which can result in a decrease in foreign direct investment inflows. This can lead to economic problems, which can ultimately lead to political instability. These consequences of contagion can demonstrate themselves in a variety of contexts. Because of the linked nature of the components that contribute to macro nation risk, it is necessary for country risk managers to take into consideration the potential implications of contagion. For the purpose of illustrating a model, this means that if one macro variable indicates risk, the entire macro environment that surrounds a multinational corporation ought to be evaluated for the impacts of that risk.

2.4 The different directions of country risk models

Gaillard (2020) identifies significant advancements in the field of sovereign risk analysis within academic research. He considers several academic models—discriminant analysis, principal components analysis, logit models, and probit models—to be more sophisticated than those employed by major banks. Following the Mexican debt crisis of 1982, Gaillard (2020) observed three main strands of research articles: 1. comparisons of country risk analyses, 2. a reevaluation of sovereign risk methodologies with increased focus on structural economic features, and 3. an investigation into the determinants of Euromoney and Institutional Investor ratings. Gaillard notes that the third strand encompasses the influential research conducted by Cosset and Roy (1991). He states, „These studies laid the groundwork for an extensive sovereign ratings literature, which flourished in the following decades."

After country risk established itself as a research field, multinational corporations formed teams and, in some cases, entire departments dedicated to conducting country risk assessments. The models used in this field diverged into two main categories: qualitative and quantitative. Both types share structured frameworks and often include identical variables. One constant in country risk research is the variety of use cases. Banks will continue to employ country risk methods to secure their outstanding loans to sovereign nations and to evaluate their overall retail banking operations in both foreign and domestic markets. Nonfinancial multinational corporations utilize country risk models to assess risks to their business operations in host countries, while scholars will persist in developing or refining country risk models for academic purposes. The notable shift will be toward increasingly integrated frameworks of hybrid models, which are already standard in certain institutional applications, such as those used by Standard and Poor's.

In academia, the evolution of country risk models has transitioned from a reliance on qualitative assessments to a greater focus on quantitively data-driven approaches, often critiquing the historical shortcomings of expert opinion models. Organizations such as Business Environment Risk Intelligence (BERI), the Economist Intelligence Unit (EIU), Euromoney, Moody's Investor Services, S.J. Rundt and Associates, and the Standard and Poor's Ratings Group have continued to employ qualitative insight methods to provide risk ratings for their clients (Howell, 2001b).

Rating-based models, which emerge from the robust, expert-driven domain of country risk research, are primarily developed by organizations that assess country risk. These organizations utilize expert methodologies to gather new data and insights for evaluating country risk. As contemporary research shifts in focus, rating-based models are less likely to be the target of academic inquiries into new country risk models. One notable qualitative model in this field is the International Country Risk Guide (ICRG) by the PRS Group, operational since 1980. It comprises 22 components categorized into three risk areas: political, financial, and economic. As already mentioned in 2.1, the PRS Handbook (Howell, 2001a; Howell, 2001b) assigns a maximum numerical value to each component, where the highest value signifies the lowest level of risk.

The framework of qualitative models often allows for the creation of quantitative models based on their variables. Economic assessments by experts can be expanded by quantitative data. The integration, therefore, of quantitative aspects into qualitative models already proceeded. The development of quantitively driven models has advanced through varied data collection processes and variables; however, the other way around, qualitative models have not yet been sufficiently integrated into these newer frameworks. The advent of machine learning and artificial intelligence holds the potential to enhance the integration of quantitative and qualitative models. In particular, models that incorporate expert opinion could be better integrated into hybrid frameworks, as algorithms can contextualize data and both critique and support the weight assigned to expert opinions.

The predictive accuracy of both quantitative and qualitative models varies depending on when the data is inserted. The most accurate model, which has been tested multiple times and consistently maintained a statistically significant result, can lose this significance when the data changes due to external factors not accounted for in the model. This is why models strive to encompass as many relevant aspects as possible, even though this presents a challenge.

Adaptability to rapidly changing environments is becoming increasingly critical. The BANI (brittle, anxious, nonlinear, incomprehensible) world referenced here necessitates a reevaluation of the priority settings for models that assess country risk as well. There must be a greater emphasis on the time required for data collection, rather than solely on data quality and the reliability of data sources. Delayed data can render quality less significant; thus, scholars must strike a balance between these two tasks in their research. Institutional frameworks, however, may be too slow, relying on quarterly or annual data publications or updates to data banks.

The model risk and uncertainty are of course also carried by an integrated model, by the risk of fat tail events and other lacks of statistical significance for certain occurrences. While the combination of both methods offers a more comprehensive assessment, the uncertainty faced by multinational corporations will persist, as not every country risk event can be anticipated. However, this uncertainty should not impede the advancement of more sophisticated assessment tools.

2.4.1 Qualitative methods

The emergence of a more globalized and interconnected world, characterized by the transnational operations of multinational corporations, has been accompanied by an increase in country risk for these corporations. Historically, the demand for expert assessment of these risks has risen at various points. The transition from a VUCA (volatile, uncertain, complex, ambiguous) world to a BANI world further demonstrates the importance of country risk assessment (Kruse, 2025).

The IMF's (2021) Vulnerability Exercise, tasked with identifying country-specific macroeconomic risks, is also moving towards the application of ML models. In the past, the Vulnerability Exercise faced the problem that differences in risk assessment methods across income groups made results difficult to compare. ML methods have been used to address the heterogeneity of crises across multiple countries. Qualitative analysis of country risk involves a sentiment analysis of all relevant information. This method allows for a comprehensive evaluation of a situation without being constrained by quantitative data. Bouchet et al. (2003) outlines six essential elements for effective qualitative analysis: 1. the social and welfare dimension of the development strategy, 2. macroeconomic fundamentals, 3. external debt evolution, structure, and burden, 4. the domestic financial situation, 5. an assessment of governance and transparency issues, and 6. an evaluation of political stability. Country risk surveys can incorporate these aspects into scenario-based questionnaires.

Expert judgment and panels provide subjective assessments of these components, although such assessments may also incorporate some quantitative insights. For multinational corporations seeking to evaluate their risk through these methods, they have the option to either purchase these insights or attempt to acquire this assessment internally through country managers or other personnel. The advantages of qualitative approaches remain significant even in a predominantly quantitative, data-driven environment, particularly regarding expert opinions. The knowledge and experience of country managers and experts can render quantitative analyses ineffective if the context of the information—something only experts can provide—is missing from the data input into the model. The previously mentioned country risk survey, for instance, generates a valuable database for MNCs that can be utilized in integrated or hybrid models. To capture context, nuances, and early warning signals, expert opinions can be crucial. While artificial intelligence aims to derive similar conclusions from sentiment data analysis, it may fall short when faced with new situations that require an understanding of subtle nuances. Achieving transparency in expert selection and weighting is essential for recreating models and testing them against new artificial intelligence models; however, this transparency is challenging for researchers to attain. Consequently, researchers often find themselves limited to comparing the results of different models.

The conclusion drawn from analyzing the directions of country risk models supports the objective of researching models capable of assimilating vast amounts of data while employing machine learning and artificial intelligence to create universal frameworks. As previously discussed, these models are hybrid in nature, incorporating both quantitative and qualitative data. However, achieving this ambition presents several challenges. Currently, there is no methodology for country risk that effectively integrates both aspects into a single model. A more pragmatic approach is to run both types of data inputs concurrently, utilizing expert opinions to validate the outcomes of quantitative models. Qualitative methods are vital, especially for assessing political institutional risks, as experts can sometimes discern unusual developments more effectively than quantitative data alone can. The future lies in complementing both approaches rather than replacing qualitative models with data-driven ones.

2.4.1.1 The significance of experts

Expertise and insights should never be overlooked; regardless of a country's quantitative evaluation, insider knowledge and the assessment of unknown variables can be crucial in evaluating country risk. Re-examining the quantitative assessment demonstrates the importance of professional knowledge in interpreting the results. One cannot consider any expert judgment as absolute, as all experts are subject to personal biases and limited by the evidence available to them. Initially, expert judgments were the preferred method for multinational corporations in assessing country risk, and modern firms continue to offer services based on expert analysis.

In a new context that is essential to the construction of country risk models, Bouchet et al. (2018) emphasizes the significance of specialists, with a particular emphasis on the function that „local intelligence“ plays. When it comes to identifying potential threats and possibilities, Bouchet et al. asserts that „local intelligence is the key.” On the other hand, acquiring information that is readily available to the public, such as from databases, research reports, and local media, can be a difficult and expensive procedure. On the other hand, although public information may be easily accessible and relatively inexpensive, it frequently suffers from uncertain quality due to the fact that it may contain information that has become obsolete which originates from central banks and financial ministries.

Open-Source Intelligence (OSINT) data collection is a strategy that can be utilized to efficiently carry out this method of gathering local intelligence. This method has the potential to encourage innovation in the development of new qualitative models because it does not necessitate the presence of a country risk manager who is responsible for maintaining an extensive network within host nations. OSINT collection, on the other hand, can allow for the acquisition of local intelligence and its incorporation into risk analysis. In the event that these approaches were implemented, the concept of experts would be expanded; yet, the function of expert-driven models might also expand. It is possible that the new group of experts will consist of individuals such as unionized workers, members of the local media, people who are now without jobs, retired workers, university scholars and students, investors and bankers, government officials, and civil servants.

2.4.1.2 The checklist method

International economic events have consistently highlighted the role of banks as pioneers in developing country risk models. Consequently, banks were among the first to create checklists for assessing country risk, which involved qualitatively evaluating the conditions of various elements on the checklist. They played a leading role in forming these checklists for nations to evaluate country risks.

Jarvis and Griffiths (2007a) referred to this checklist method as the Catalogue School of first-generation approaches, critiquing it for its overly simplified worldview. Their research traced the evolution from the first-generation checklist method to more sophisticated approaches. They noted that the depiction of political processes and markets was overly simplistic and failed to consider „the state as an enabling agent of commercial practice." They classified the second-generation methodologies as the System-Event School. This generation aimed to correlate system characteristics with the likelihood of various political risk events occurring. This school emphasizes recognizing events that can affect regime stability and undermine the governing capacity of the incumbent regime, as well as systemic characteristics that foster political events while detracting from system stability, political maturation, and legitimacy. Political risk includes events such as social or political upheaval, expropriation, labor disputes (including strikes), challenges related to profit repatriation (such as currency restrictions), and the enforcement of import limitations.

The third generation of political risk approaches focuses on the distinction between method and theory. They prioritize informed microanalyses above big theoretical correlations, emphasizing the significance of context and concentrating on project-level analysis. Despite their distinct categorization and varied insights, these methodologies collectively reject the overarching theoretical heritage of political science. Third-generation methodologies for political risk prioritize technique over theoretical frameworks. Innovative Fourth-Generation Methodologies. Various projects aim to establish systematic methodologies for identifying precursors to various international risks related to food security and famine, ethnic and religious tensions, civil conflict, interstate hostilities, energy crises, and environmental sustainability (Jarvis and Griffiths, 2007a).

2.4.2 Quantitative Methods

The initial quantitative models that yielded statistically significant results paved the way for a diverse group of scholars who advocated for further research using this method (Balkan, 1992), which subsequently led to the development of various quantitative methods (Nath, 2009). Recently, quantitative methods have not only gained popularity but have also become more complex and advanced. Although a universal and flawless method has yet to be discovered, research remains focused on identifying significant quantitative methods. Scholars continue to seek advancements across different quantitative approaches (Brown et al., 2015). Younger researchers are revisiting political risk, such as Hetou (2019), who examines the problems with mathematical models in social science, noting that model distributions do not represent the real world, yet still attempting to integrate quantitative risk methods into their own models.

Bouchet et al. (2003) summarized several quantitative models in his book:

Discriminant analysis: This method aims to classify countries based on their likelihood of defaulting, expropriating, or engaging in other actions perceived as unfavorable for investments. This classification was achieved by establishing group classifications, collecting data on these groups, and identifying the key characteristics that effectively differentiate between them. Bouchet et al. highlighted a significant issue with this method, stating, „The problem is that the standard deviations of x1 and x2 may be so large that the two groups will overlap, such that some of the defaulting countries will have higher Z-scores than those of the non-defaulting countries." Although cutoff values can help reduce misclassifications, the method still relies (in a practical application) on the qualitative input of an analyst to assess the model's outcomes.

Logit and Probit models classify countries as either defaulting or non-defaulting by utilizing binary variables. These models are appropriate for assessing political risks that have dichotomous outcomes, such as expropriation or debt default. Although Bouchet et al. (2003) references several scholars who have effectively employed this method, he argues that it is insufficient for a comprehensive country risk model. He states, „The effects of the explanatory variables can differ from country to country and change over time. For example, a debt service ratio of one form or another enters many of the foregoing models with a negative sign, and, based on the signaling hypothesis, it can reasonably be argued that the high debt reflected in high debt service ratios should be viewed as a good rather than a bad credit signal. Arguments such as these hold for many of the variables that enter the models. Thus, as effects vary from one county to another and over time, it is difficult to interpret the results."

Regression analysis: This will be discussed further in section 2.4.2.1.

Monte Carlo simulations: Country risk modeling can utilize Monte Carlo simulations to calculate the distribution of investments across various projects, thereby estimating risk. In a Monte Carlo simulation, the effects of political risk are estimated directly. The role of the political risk analyst involves identifying relevant variables and determining the probabilities of forecast errors. However, Monte Carlo simulations have yielded mixed results in country risk research and have faced criticism from some scholars. Bouchet et al. concludes his review of this method by stating, „Monte Carlo simulation has several major drawbacks. It requires constructing a suitable model and obtaining probability distributions for a large number of variables. This task is extremely challenging and costly in terms of programming and machine time. Therefore, full-scale simulations are generally not worthwhile unless they are conducted for large and expensive projects." While the latter criticism may be less relevant given modern computational power, the challenge of constructing an appropriate model with distributions for numerous variables remains valid.

Value at Risk models: The purpose of these models, as the name suggests, is to calculate the degree of confidence over a specific time frame, indicating how much value in a portfolio, and consequently in an investment, may be lost. The method can be used for single-asset portfolios as well as for two-asset portfolios, and it uses the investment value and degree of confidence to calculate the possible loss over a certain period of time in the portfolio. The problem is that Value at Risk models are assuming normal market conditions and are using a joint normal/log-normal distribution, while „extreme conditions are considered separately."

Additional methods include principal component analysis, nonlinearities and nonparametric estimations, and artificial neural networks, which will be further explained in section 2.4.2.2.

In his 2018 book, Bouchet et al. reiterates the importance of quantitative methods in the chapter titled „The Growing Role of Quantitative Measures of Country Risk and the Limitations of Models." He outlines six main features of quantitative methods: 1. Indicator/variable screening, which seeks to identify explanatory variables; 2. Indicator threshold setting, which involves establishing thresholds for quantified risk level scores; 3. Assigning relative weights to indicators; 4. Understanding the limitations of the model; 5. Avoiding overreliance on checklists or predetermined indicators; and 6. Incorporating scenarios in prediction models.

2.4.2.1 Regression analysis

A strong criticism of multiple regression models for forecasting comes from Armstrong and Green (2018), who state that „multiple regression approaches violate evidence-based forecasting principles." They considered multiple regression analysis forecasts useless and were, in general, critics of data models, including neural networks, though their views on the latter are not shared here due to differing opinions.

To elucidate the research approach, it is necessary to revisit several questions from the preceding section. With the development of quantitative approaches for country risk models, regression analysis has become a frequently employed technique that led the checklist method to be used nearly completely to institutional users. The dependent and independent variables of country risk regression models exhibit heterogeneity; however, they frequently share similarities in nature. In the context of country risk related to economic and financial factors, the dependent variables typically indicate the security of loans and the financial stability of a nation. The impact on GDP is frequently utilized as a dependent variable in such models. Political or other country risk models that utilize regression analysis face challenges in determining variables such as historical wars, conflicts, changes in political regimes, and terrorism. Still, regression analysis is a frequently utilized instrument in country risk assessment. The variables in country risk assessment frequently exhibit correlations and yield favorable outcomes when subjected to regression analysis. Bouchet et al. (2003) underlined that regression analysis had a more empirical approach then Logit and Probit model, by developing a theoretical model and „tests its ability to explain the phenomenon in question."

The primary and most impactful factor in country risk assessment is the digitization of risk models and the advancement of data analytics. This thesis considers two trajectories for data collection progression for regression analysis. Primarily the process of only extracting quantifiable information, which is then use for regression analysis and other quantitative methodologies. Secondarily, qualitative data which to be deemed suitable for neural network analysis and other methodologies in artificial intelligence, will still not be used in regression models. In the near future, one expects artificial intelligence to become a crucial component in country risk analysis. This will make country risk models that rely solely on regression analysis obsolete. More likely statistical aspects of a regression model will be used for the math used in artificial intelligence The qualitative processing of data through neural networks offers enhanced data accessibility that the regression analysis can't compete.

In terms of criticism, E. Pietrabissa (1987) of the Banco di Sicilia Foreign Relations Division authored a correspondence concerning the issue of regression analysis and weights. The inquiry pertains to the potential existence of an objective criterion for ascertaining the weights. The evident conclusion is that an objective criterion is nonexistent, rendering any rating system susceptible to the arbitrariness associated with the employed technique. However, it is essential to critically assess the notion of just employing qualitative analysis: Despite the complexity and systematic nature of such research, they yet engender skepticism, leading to the lingering question, if they should choose Country X or Country Y.

However, the advantage of qualitative risk models is that saved data can be retrospectively evaluated to modify variables. Regression analysis and other quantitative methods explicitly store data for the selected variables. When you individually acquire a regression dataset for a certain variable over an extended timeframe, you cannot use it for other variables intended for quantitative research. However, one can select qualitative data from a range, even if it pertains to a specific variable. You could utilize the white noise from that dataset for additional variables. This benefit is particularly advantageous when the qualitative analysis pertains to natural language models within a neural network. Neural networks may identify certain segments of a dataset and adapt them for a new variable. Although similar actions can be performed on quantitative datasets, it is probable that the white noise data fails to yield the necessary information for a variable.

2.4.2.2 Neural Networks

The literature on artificial neural networks (ANNs) continues to grow, including research on their applications in data science (Rothman et al., 2018; Thompson, 2024). However, the mathematics behind neural networks has existed since the last century. Shadbolt and Taylor were already using neural networks in 2002 for the analysis of financial markets.

Artificial neural networks are modeled after biological brains (Aggarwal 2018; Ananthaswamy, 2024; Haykin, 2009). Analogous to biological neurons, each node in an artificial neural network aggregates and processes incoming signals, subsequently transmitting the output to neighboring nodes. Artificial neural networks are typically structured in feedforward layers, where input data is introduced to an input layer and subsequently processed through several hidden levels before reaching an output layer. Artificial neural networks with numerous hidden layers are referred to as deep neural networks. Artificial neural networks are trained by adjusting the weights of the connections to reduce the discrepancies between the predicted and target data labels. Upon completion of training, the artificial neural network may predict the output for previously unencountered input data. A primary problem among AI practitioners and researchers is the interpretability of trained artificial neural networks. Currently, ascertaining how a certain neural network arrives at its predictions is challenging. In certain domains, this is not a concern. In certain fields, like medical data analysis, physicians are hesitant to employ a neural network without a comprehensive grasp of the mechanics underlying the network's predictive processes. Artificial neural networks necessitate substantial datasets for effective training, which may not be accessible for all assets or markets.

In their study paper, J. Yim and H. Mitchell (2005) concluded that hybrid networks would be beneficial for researchers, policymakers, and anyone interested in early warning systems. This outcome stemmed from studies involving neural networks and hybrid neural networks, with the latter demonstrating superior performance in this context. It is important to note that they utilize a single hidden layer including only two nodes. Moreover, they employed a restricted number of variables. In their publication.

Bouchet et al. (2003) critiqued neural network implementation, stating, „A significant issue with neural networks is the absence of universally accepted methodologies for determining the network architecture, including the selection of the activation function, the quantity of hidden layers, and the number of units, among other factors." Moreover, the network parameters are generally acquired by minimizing the sum of squared errors, and due to the potential non-global convexity of the objective function, numerous local minima may exist. Conducting significance testing is extremely challenging.

Cimpoeru's (2011) research on the application of neural networks in credit risk assessment indicates that „a review of the specialized literature reveals that neural networks produce superior results compared to other classification methods, such as multivariate discriminant analysis or logistic regression, in credit risk assessment scenarios." The conclusion derived from the specialized literature is corroborated by the case study she conducted. However, it's important to note two more points of criticism stated by Kosmidou et al. (2008). First, Kosmidou stated the required computational power required to conduct neural network analysis on a larger scale could be a problem. With the developments since the publication in 2008 in average available computational power, this point cannot be considered validated. Second, „the inability to provide explanations of the neural network's result." This criticism still holds up, but the advantages of a non-linear model, which can be optimized soon by developments in the area of computational efficiency through machine learning and artificial intelligence, mean the research of neural network models for country risk models should continue as in this research.

2.5 The Black Swan/Fat Tail Event

Integral to any form of risk analysis is the concept of the Black Swan or Fat Tail Event. These terms refer to the risk associated with unplanned or unpredictable events that can significantly alter the realities that a country risk model aims to assess. Every model, whether quantitative or qualitative, must recognize that its outcomes are inherently incomplete due to the possibility of a Black Swan event, which can render the assessment obsolete. Nonetheless, developers can significantly reduce the risk of such events to improve the applicability of a country risk model during its development. This approach involves incorporating a variety of aspects related to country risk, which in turn addresses the challenges present in quantitative techniques. Furthermore, qualitative approaches face similar challenges concerning the volume of input data. In expert analysis using checklist methods, a key issue is determining which variables should be prioritized or weighted.

David Vose (1996) raised questions regarding the inclusion of rare events—his terminology aligns with Black Swan or Fat Tail events—within risk analysis models. He posed the question of whether rare events can be effectively modeled and, if so, whether they should be included in a model that primarily addresses general uncertainty. He noted that the expected impact of a rare event is influenced by two factors: the probability of its occurrence and, if it does, the possible distribution of its impact. Vose observed that, generally, determining the distribution of a rare event's impact is more straightforward than estimating the probability of its occurrence. He cautioned against a common mistake: incorporating rare events into risk analysis models that focus mainly on general uncertainty. Even today, Vose's insights remain relevant. He emphasized that the challenge often lies in accurately determining the probability of such events, which poses a significant hurdle for analysts.

Fat tail or black swan events were forcibly brought into the concerns of country risk managers in the years 2016 and 2024, which coincided with the election years of Donald Trump as President of the United States of America. An entirely new level of uncertainty is introduced by the unpredictable and erratic behavior of Donald Trump, which is separate from the madman tactic employed by Richard Nixon. At the beginning of the year 2025, President Trump put into effect a tax system that was designed to solve the trade deficit that the United States was experiencing. The financial markets, the value of the dollar, and the overall economic outlook were all badly impacted as a result of this move, which was met with considerable criticism from respected analysts. On the other hand, if a country risk manager had been able to anticipate these events through modeling or their own experience, then Trump's choice to stop tariffs for an extended period of time would have been just as surprise as the imposition of the levies. Significant hurdles are presented to country risk managers by the timing of tariff announcements and suspensions, as well as the intensity of these actions.

2.6 The Future of Country Risk Assessment

The aim to create a country risk model, which serves as an early warning system, is as old as the field itself (Tümpel, 1987). As the global environment for multinational corporations shifts into a BANI world characterized by increasing risks, assessment tools for business cases are also evolving. This includes country risk assessment, where machine learning and AI are advancing the field. However, much of the progress made in the field is done behind closed doors.

In September 2023, the energy website Rigzone stated that Standard Chartered (SC) introduced a tree-based model aimed at forecasting the price of Brent Crude Oil, named Scorpio. The model integrates technical variables, pricing data, positioning metrics, worldwide inventories, demand, and import and export statistics, together with non-oil indicators such as the US dollar, PMI, and other macroeconomic factors. SCORPIO demonstrated a statistically significant directional accuracy of 67.3 percent. The SCORPIO model utilized various data sets, yielding outcomes that ranged from significantly relevant to negligible and non-explanatory. The sentiment data, including news material, was utilized; however, for the SCORPIO model, this period did not provide additional value to the model on a daily to weekly basis.

SCORPIO utilized back-tested predictive performance from a preceding period. Performance is assessed using value-based metrics, such as mean absolute error, and directional metrics—categorizing outcomes as up, near zero, or down—while employing classification and evaluation metrics. According to research by Standard Chartered: „We construct error bands for all predictions utilizing quantile regression techniques (employing identical features).” Standard Chartered indicated they can produce a daily report that elucidates the origins of price fluctuations, categorized by topic groups. However, the report noted that the SCORPIO model cannot anticipate Black Swan events (Exarheas, 2023). The model developed by Standard Chartered employs indicators for country risk assessment and incorporates modern machine learning techniques. Standard Chartered specifically designed the model to forecast Brent prices, but methodological advancements also impact the field of country risk modeling.

GeoQuant exemplifies one of the most sophisticated applications of regression analysis and artificial intelligence technology for assessing country risk. As a Fitch Solutions enterprise, GeoQuant creates real-time models for anticipating country risk, demonstrating progress in a series of white papers. This research is notable for its high number of data points per variable (250), its regression models, and its application domain, primarily financial markets. Being a private entity, not all of GeoQuant's data processing and innovations are accessible for further research; nevertheless, indications suggest that GeoQuant is establishing benchmarks in country risk assessment by utilizing quantified open-source data. In the white paper „Forecast Models of Sovereign Bond Rates,” GeoQuant concluded that „objective, systematic data is scarce and high-frequency data is nonexistent.” They developed an algorithm that „continuously analyzes high-frequency text data globally and incorporates it with structural risk factors“ (GeoQuant, 2018).

The white paper outlines a straightforward statistical model that utilizes GeoQuant's daily top-line political risk indicators to predict daily yields on ten-year bonds across twenty nations. Key indicators assess governance, societal conditions, and security risks. The approach suggests that both daily fluctuations in risk and broader risk trends influence market behavior; therefore, it integrates a daily score with a moving average. GeoQuant concludes that the field of risk management has been lacking in objective, high-frequency country risk data. The political risk score is calculated from twenty-two political economics factors, updated daily, and combined using a proprietary weighted model. According to GeoQuant, „Current political risk data is plagued by three issues: subjectivity, infrequency, and an excessive emphasis on outcomes rather than underlying drivers" (GeoQuant Macro-Economic Policy). The risk score reflects projected exchange rate variations tied to ongoing policy changes and political events, rather than solely relying on new economic or financial information. GeoQuant's risk data is scaled from 0 to 100 (GeoQuant, 2018). While GeoQuant presents a state-of-the-art model with quantified data for country risk assessment, it also highlights that such assessments for multinational corporations remain largely inaccessible, hidden behind private consulting firms.

GeoQuant employs rolling models to enhance their forecasting capabilities: „To prevent overfitting and the occurrence of false positives, we produce forward-looking forecasts with rolling models. We estimate initial model parameters using six months of data and then predict the subsequent period. The next day, we revise the model and generate updated forecasts. As a result, the model's projections are primarily out-of-sample, predicting future bond yields based on historical data. The back-test of GeoQuant indicators' forecast reliability is established through a rolling regression forecast. This regression begins after the initial 190 complete data points have been collected and calculates the coefficients for that specific day, focusing on days when the model provides signals, such as „the largest 5% of movements"" (GeoQuant, 2018).

The interval between politically relevant news and investment responses can vary significantly. In highly developed markets, such as the United States, which feature liquid securities and knowledgeable investors, a minimal delay can be expected. The model ideally requires a lead time of just one or two days. In contrast, the responsiveness of illiquid emerging market bonds may be slower because a substantial portion of investors are international. In their conclusion, GeoQuant emphasizes the importance of monitoring relative political risk between markets perceived as substitutes. Despite treating these markets as independent, the model may reveal an inverse correlation, where relative risk influences cross-country capital allocation. Additionally, by incorporating other dependent variables, such as equity, currency pairs, and corporate debt, GeoQuant seeks to model more complex relationships among its variables. For example, analyzing how rising societal danger interacts with governance risk scores may reveal risks that surpass the combined effects of these factors. Risk scores may reveal risks that surpass the combined effects of these factors. The Institute for Strategic Studies identifies a novel risk associated with significant language models: the emergence of new models capable of producing substantial amounts of impactful propagandistic material.

2.7 The Quest for relevant data needed for Country Risk Assessment

In a data-driven world, the challenges posed by inadequate data appear paradoxical, considering the extensive production, collection, and utilization of data. Bouchet et al. (2018) states, „Country risk analysis is as good as the information it relies on. Compared with the 1980s or even 90s, country risk analysts do not currently face a deficit of economic intelligence sources—indeed the contrary is nearer the truth. Rating agencies, multilateral institutions, merchant banks, and thinktanks produce sophisticated and comprehensive databases and rankings." He argues that quality and accuracy alone are indicators of country risk. A country that does not provide sufficient data is therefore inherently at higher country risk.

Data quality varies significantly, encompassing aspects such as validity and informational value. Researchers frequently encounter issues of missing, outdated or even false data when validating or evaluating certain economic models. Country risk models face similar challenges, leading many assessments to rely on expert analysis, which often limits accessibility. The official databases of multinational institutions and the databases of national central banks do not always provide the necessary information for a new model, and they are often unable to deliver it in a timely manner.

The rise of open-source intelligence (OSINT) data is advantageous for scholars across various fields. Institutions like the World Bank, OECD, and the Federal Reserve commonly utilize this accessible data in their national research. In addition to their proprietary internal data, these institutions also gather OSINT data to create new databases for research or to address specific research inquiries.

Scholars and practitioners in the field of country risk must adopt new methodologies to pursue relevant data for country risk models. The aforementioned organizations can both discard and generate data in the information age. Key considerations in data collection include timespan, quality, and quantity. Private institutions cannot directly equate new country risk data with public government data. While expert opinions used in institutional country risk assessments are generally timely and accessible through institutional questionnaires, the rapid generation of quantitative data remains more challenging. The pull and push factors of capital are complex and can be triggered by the increasing hypersensitivity of the market.

For institutional practitioners, the technical aspects of the information process are less intimidating. Data science tailors programming languages like R and, notably, Python, which offer various tools for efficiently integrating country risk data. As one will demonstrate later in this research, these programming languages play a vital role in implementing new techniques for collecting country risk data.

2.8 Open-Source Intelligence (OSINT)

Open-source intelligence (OSINT) is a term utilized in both investigative journalism and the intelligence community to describe the collection of publicly available data. As defined by the Director of National Intelligence (DNI), „OSINT is intelligence derived exclusively from publicly or commercially available information that addresses specific intelligence priorities, requirements, or gaps" (Office of the Director of National Intelligence, 2024b). Currently, the internet space hosts a significant portion of the data collected through OSINT methods. According to CMI LLC, a market research and advisory company, the value of the OSINT market was estimated at $5,449.23 million US dollar in 2021, with a forecast of reaching $36,241.24 million US dollar by 2030 (CMI LLC, 2023). This growth is largely attributed to the widespread use of social media; however, OSINT data also encompasses reports from think tanks like Oxford Analytica (2018, 2023, 2024), government documents, and other information pertinent to country risk analysis. The application of OSINT data is already widespread among the global intelligence community, encompassing both private and public sectors, as well as in investigative journalism, academic research, and business intelligence (Bazzell, 2018). The aims and limitations of OSINT vary across these different applications.

One field that has experienced significant advancements is alternative data, particularly in the area of OSINT data. Such data includes unconventional information and various data collection techniques, such as analyzing movements in satellite imagery or creating new databases by monitoring social media platforms for spikes in activity. Hedge funds and other institutions use this data, which is also available for purchase from data brokers.

The methodology of data collection is as crucial as a model's processing technique. OSINT data can be both quantitative and qualitative, and it can exist in either preprocessed or raw forms. The sources of OSINT data are diverse, ranging from validated information to outright falsehoods. The latter can be especially challenging to verify, complicating scholars' efforts to develop OSINT models that depend on the most exclusive and timely information. This challenge is particularly pronounced in government, politics, and security fields, where the prevalence of bias and misinformation has increased significantly in recent decades. Therefore, primary sources should include government websites and reputable news outlets, integrating government statements and verify news articles into the data collection process.

The availability and reliability of data from OSINT sources create significant challenges for researchers, as discussed in section 2.8.1. Verification can often be problematic, and the rise of AI-generated websites and other sources further complicates data collection. The presence of false data or data with strong biases is a concern, as is the issue of placeholder data, which can lead to improperly weighted databases that distort the input of variables.

The International Monetary Fund (2025) offers reliable country risk data, publishing a comprehensive array of economic information about its member countries. Since 1995, the IMF has upheld data dissemination standards designed to guide its members. These standards are especially stringent for countries with access to international capital markets. Additionally, since 2002, the IMF has conducted debt sustainability analyses for each member country, serving as a tool to better detect, prevent, and resolve potential crises (Bouchet et al., 2018).

In addition to the International Monetary Fund, the World Bank provides a substantial database for country risk data, primarily focusing on macroeconomic indicators. As a major lender, the World Bank established a Debtor Reporting System in 1951 to monitor long-term public or publicly guaranteed debt. The World Bank’s International Debt Statistics, its governance assessment data, and its evaluation of business conditions supply valuable and reliable information for country risk models. Alongside the data and assessments offered by the IMF and the World Bank, which are discussed further in the context of Open-Source Intelligence, the Bank for International Settlements also monitors the activities of central banks, producing assessments that serve as important inputs for country risk analysis (Bouchet et al., 2018).

However, both the IMF and the World Bank face challenges related to the lengthy timespan of their data collection and public release processes. While other OSINT sources may lack the reliability and sophistication associated with traditional datasets, they can be gathered much more rapidly. The risk lies in the potential information overload that OSINT can create for country risk models relying on this type of data. Additionally, as was indicated earlier, Bouchet et al. (2018) also stressed the necessity of local intelligence when it comes to evaluating the danger that a country faces. He made the observation that „risk analysts, however, will never match the volume and quality of information and economic intelligence possessed by local residents." Despite the fact that risk analysts rely on secondhand reporting, local residents have a profound relationship to the sociopolitical, cultural, and economic risk variables that need to be recognized. The former group is comprised of a small number of individuals, but the latter group is comprised of a large number of people and exemplifies the concept of the „wisdom of crowds." Bouchet et al. (2018), on the other hand, did not investigate the possibility that country risk managers may acquire and assimilate this local intelligence by utilizing sophisticated OINST methodologies.

Ethical and legal concerns surrounding OSINT data are important; however, these issues are not explored further in this research. When developing new models based on extensive OSINT data, scholars and researchers need to be cognizant of these concerns and should seek legal assessments of their data collection processes to avoid turning the risk assessment model into a risk of its own.

2.9 The difference between missing data and data for sale

The important distinction exists between missing data, which signifies an imperfection in country risk assessments, and hidden data. Open-source intelligence provides access to missing data, but it does not integrate into country risk models. For instance, expert assessment can compensate for the absence of a country's inflation rate publication. The issue of missing data in country risk primarily stems from delays in statistical reporting by government entities, particularly in countries with weak reporting standards.

Conversely, data for sale presents a more formidable challenge. In the context of OSINT, data for sale complicates efforts to address information inequality compared to other models. Enhanced funding for these models can facilitate the acquisition and utilization of additional OSINT data. However, the availability of data poses constraints on this research. A significant advantage of a universal country risk model is its capacity to incorporate supplementary data by addressing situations where data can be purchased and integrated. Nonetheless, country risk models employing regression analysis with variables such as GDP cannot assimilate new data; they can only alter the data source or devise a new regression model.

Data for sale still falls under the OSINT definition because its collection does not require covert methods. This data is publicly and legally available for purchase, and accessing it does not breach confidentiality. It is crucial to understand that open does not imply free. The essential aspect of OSINT lies in the collection method.

3. MATERIAL AND METHOD

The following methodology illustrates how the CR model is built to confirm the research hypothesis. The model uses a data collection logistic to create a new, individual, and universally changeable database. The created logistic includes the developed script in Appendix 8.2. The server structure is the server that runs Changedetection, the IONIS server that runs the MySQL database, and the computational hardware that locally runs the model seen in Appendix 8.3. The additional assessment for statistical significance is represented in Appendix 8.4.

This section will further introduce the variables of the model, which are representation of previous developed models in country risk assessment. They are covering the most important aspects of country risk like government, economic stability, and further necessary parts of a full model. Furthermore, the section will outline the sentiment analysis used for creating the grounds for the model in Appendix 8.3 and the neural network trend prediction that forecast a negative or positive trend for a certain variable or the whole country.

3.1 Data integration into the CR model

The duration between the accumulation of country risk and its materialization varies differently. In hindsight, numerous scholars often acknowledged the shortcomings of certain country risk models, as the threat may have been anticipated had the model incorporated an additional variable or source of information. MNCs have recognized that protests and political changes can occur rapidly, particularly with sociopolitical risk, but have yet to discover a way to efficiently collect the data for risk assessment. A negative comment or incident related to corporate operations can quickly mobilize a large number of individuals via social media to protest against the company. In response, politicians may transition from being business-friendly advocates to being staunch adversaries of the enterprise. Country risk models must accurately reflect the current risks to ongoing corporate activities.

In an already strained corporate climate, monthly or even quarterly data gathering for sociopolitical risk is likely ineffective. Given that social issues related to environmental concerns are significant for multinational corporations serving a vast consumer base, the creation of a more rapid evaluation methodology becomes warranted. Moreover, additional aspects of country risk, such as the potential for a fluctuating security environment, may increase the necessity for expedited models. A terrorist incident in Germany resulted in an immediate escalation of border security measures. This has led to longer supply periods for commodities traversing borders within the European Union. Allianz Trade reports that these changes resulted in a 1.7% rise in transport and import taxes (Allianz Trade, 2024).

The global security situation is precarious. The activities of drug cartels in Mexico and South America render a heightened response from the USA more probable. Terrorist acts and Russian sabotage actions pose a significant and imminent threat in Europe. In Asia, some conflicts possess the capacity to escalate, including those in Myanmar, Kashmir, and the danger to Taiwan's sovereignty. In Africa, the intensification of persistent crises related to food scarcity, civil unrest, and the effects of climate change is evident. The global interconnectedness of the contemporary world necessitates the acquisition of rapid data for country risk assessment in any given situation. The domain of country risk should focus on optimizing data collection methods for efficiency, while also refining and integrating this data into various country risk models. This principle applies regardless of the type of country risk model used. A traditional checklist paradigm, despite infrequent practical application, should seek methods to gather more timely data. The neural networks employed in this research can only be effective if trained with precise and timely data that exhibits a consistent upward trend in the model. To develop a model that can be comprehensive and universal, five countries were selected that should cover multiple continents, various cultures, and important ongoing political developments within the country. The countries were selected at the authors' discretion and are not inherent to the model, since its purpose is to be applicable to any country in the world.

Country	**Number of websites monitored**
Vietnam	110
Germany	164
Mexico	173
Ghana	150
Nigeria	211
Total Countries: 5	**Total websites monitored**: 808

Table 2. Sample selection. Source: Authors elaboration (2025)

Historically, the timeframes for country risk models have been monthly, quarterly, and annually. Regression analyses based on data such as GDP, trade balance, and other statistics typically published by government agencies can only be obtained and evaluated during certain periods. The previously mentioned data is highly pertinent for country risk evaluation. Nonetheless, although a country's GDP can solely be evaluated through the publication of official statistics by government agencies, during the GDP assessment period, news magazines, export reports, and other information sources will already evaluate critical components of the national economy. This data can provide multinational corporations with an image of a host government's economic condition. Future research in country risk assessment should explore innovative methods for the extensive collection of this data and, additionally, how this predominantly qualitative data might be quantified. The methods employed include web scraping of news sites, blogs, government websites, and various other data sources. Open-source intelligence, however, enhances the potential for acquiring more timely and inventive data at new levels. The success of research on country risk modeling will also depend on the financing of further research initiatives. Well-funded research initiatives may incorporate satellite imagery, now accessible to private citizens, for the purpose of data collection. These categories of data sources are collectively referred to as alternative data sources.

3.2 The Variables

The variables represent the different aspects of risk that researchers or practitioners consider important in the context of country risk. Given the variety of country risk, the number of variables throughout the history of country risk research is extensive. Classic variables include a country's GDP and national debt (Kennedy, 1987). Regression models, in particular, focus on selecting independent variables that best interact with dependent variables for explanatory purposes. However, even qualitative models involve the selection of variables that reflect desired outcomes, which can introduce bias from the model's author.

Furthermore, it is crucial to evaluate whether the data basis for the variables includes a sufficient number of data points and whether these points correlate with the data points of other variables within the same model. Occasionally, this can lead to limitations in the data available. An average analysis of the variables used throughout the history of country risk likely reveals a preference for certain variables in country research. Two main factors influence this trend. First, certain variables, such as GDP, are better suited for providing a general overview of a country's stability, particularly regarding economic stability. Second, the early history of country risk is closely associated with institutional models, and the variables employed in those models paved the way for academic research, which often reused these variables to enhance model quality and outcomes (Somerville and Taffler, 2001).

While a regression model seeks to establish a strong relationship between an independent and dependent variable, it is important to note that this model, which aims to address non-linearity issues, does not rely solely on regression between the variables. In qualitative assessments of country risk, the aspects considered are of greater significance, suggesting that the selected variables should encompass as many dimensions of country risk as possible, without necessitating statistical correlation or regression among them. The variables should address key aspects that country risk researchers have identified over the last decade, including political, economic, and security factors. Additionally, the variable related to ecological risk has gained importance in country risk assessments recently. Factors such as renewable energy initiatives and green policies of multinational corporations are increasingly relevant, as a non-eco-friendly company may encounter challenges with financing or project approvals in a host country.

The variables must maintain a balance, meaning that each variable should be equally represented with data for all assessed countries. However, the sources of data for these variables can be uneven, as many originate from various news outlets, which may cover topics disproportionately, especially in smaller countries. Collecting data from news sources regarding politics, governance, and the economy is generally easier than sourcing information from specialized energy-related websites. Nonetheless, these specialized sources are crucial for specific variables.

The model examining what contributes to a country's stability begins with the first variable (outlined in 2.2.1), which gathers data on political and governmental stability and progress. The second variable (outlined in 2.2.2) focuses on the economy, collecting information about economic advancements within the country, such as national debt levels and foreign direct investment inflow. However, this data is primarily qualitative, as it relies mainly on monitored news sources for input. The third variable (outlined in 2.2.3) addresses societal issues, aiming to reflect problems within the country that could indicate the risk of civil violence or unrest.

The fourth variable (outlined in 2.2.4) is dedicated to environmental assessment. In conjunction with the fifth variable (outlined in 2.2.5), which pertains to energy, this variable considers a country's energy security—an essential factor for both political and civil stability, as well as the country's capacity for domestic production. Variable six evaluates (outlined in 2.2.6) legal stability, examining corruption or the lack thereof within the legal system to assess the reliability of contracts signed in the country and the regulatory stability affecting multinational corporations operating there.

The seventh variable (outlined in 2.2.8) focuses on security, analyzing threats such as terrorism, military conflict, organized crime, cybersecurity, and any other security-related issues that could jeopardize MNC operations. The theoretical framework of this model assigns equal importance to all variables, despite their potential lack of statistical correlation. Given the same amount of input, it cannot be guaranteed that each variable provided consistent data throughout this thesis, as different websites have varying update frequencies.

To identify a model that addresses the linearity problem and employs non-linear machine learning methods offers the additional advantage of covering a diverse range of aspects, similar to the earlier expert checklist methods (Eaton et al., 1986). This implies that the model can later incorporate more variables without requiring an analysis of the relationships between them. This flexibility not only makes the model universally applicable but also scalable to meet the specific needs of a multinational corporation. The variables described in this section are used in this research to reflect a wide array of country risk sources without dividing the data into self-manipulating sizes. Consequently, each variable encompasses multiple dimensions of risk. Kennedy (1987) noted that a component approach is a systematic qualitative model designed to quantify and correlate the fundamental elements of political risk. This methodology identifies the structural sources of political risk and aims to quantify the variables objectively while still requiring some degree of objective-subjective interaction. A component model is not only more objective and theoretically sound than expert-generated opinion approaches, but it also provides the advantage of identifying sources of political risk and allowing for a more precise assessment of their potential influence on the enterprise. Formal-empirical observational models, similar to component approaches, focus on quantifying the structural determinants of political risk; however, they avoid subjective analysis, setting themselves apart from both expert-generated opinions and component methodologies. Only rigorously tested empirical and statistical observational data are employed, producing quantitative scores for international comparison (Kennedy, 1987).

3.2.1 Governance (Political)

The governance variable aims to aggregate political and governmental data. The complexity of statecraft at both international and national levels generates extensive input for political risk within country risk models. Robock's (1971) article on political risk focuses solely on this aspect, excluding the later-developed variables of country risk assessment. He noted the global political risks facing corporations and the inadequate management practices for identifying and overseeing such risks. Erb et al. (1996) analyzed the largest country risk assessment institutions. All of them included a variable linked to the government and its influential spheres within a country. Marchetti and Vitale (2014) even aimed to make political risk assessment global by testing „the relevance of a globalization variable for political risk assessment." Many contemporary managers continue to view their companies' operations as disconnected from the political landscape in which they operate. In host nations, and often within their organizations, management tends to overlook the political ramifications and the broader political context of their activities. Furthermore, even those tasked with monitoring political risk can be surprised by its manifestations. Management often relies on risk assessment firms and their reports, which depend on expert opinion; however, these reports frequently omit data that is specific to their enterprise and accessible through public sources.

The political transformations, implications, and intricate global political networks of the 21st century have significantly complicated international politics and statecraft. The dissolution of colonial powers and the emergence of new independent states reconfigured the global political landscape, greatly altering the world in the latter part of the previous century. Currently, the world faces the rise of China and other developing nations, which seek greater shares of global political influence. This factor influences many economic aspects of a country's risk assessment. While political conditions differ from one country to another, some political effects on market conditions exhibit international similarities from an economic or legal perspective. Risk assessment should be conducted generally in the data collection process, but the data input for the variables must be tailored to each unique case. For instance, neighboring countries may have strained relations with one another. Therefore, companies must exercise caution regarding their affiliations with governments and gather data that is specific to each situation.

That political risk plays an important role for MNCs is also recognized by the officials who govern countries. Condoleezza Rice and Amy Zegart co-authored Political Risk (2018), which is notable since Rice served as the U.S. Secretary of State.

Measuring certain political risks, such as corruption or expropriation, is still difficult. Jessen (2012) attempted this in the context of corruption in the oil and gas industry by breaking down the broader field of corruption in the political risk context into an industry-specific problem. Shotts (2015) developed a model specifically to evaluate the threat of government expropriation of MNCs in host countries.

3.2.2 Economy

The affluence and destitution of nations are closely linked to the global economic system. The global political landscape over the past century has largely been influenced by American hegemony, which has shaped various aspects of the global economy, including the dominance of the US dollar. Currently, scholars are facing a complex situation due to a global shift toward a more multipolar world. The economic landscape is rapidly changing, driven by China's rising geopolitical influence, the emergence of shifting political factions, and the evolving role of BRICS. This environment has led to a recurring return to outdated nationalistic economic perspectives, resulting in a rise in protectionism. Multinational corporations are affected by fluctuations in global economic conditions, and the hyper-interconnectedness of supply networks combined with frequent worldwide demand may expose these corporations to risks tied to their national economies (Bouchet et al., 2018). Most country risk models concentrate on economic or financial components, or at a minimum, incorporate them in their evaluations of country risk. The volume of information has increased significantly due to hyperconnectivity.

Sovereign debt has always played a significant role in determining country risk. The findings of Berganza et al. (2004) include that an increase in debt burden caused by an unexpected real depreciation raises a country’s risk premium. The important role of sovereign debt default can be further evaluated under this variable. Gilliard (2020) states that, in terms of country risk ratings, „more than 60% of misratings were caused either by an expropriation or by a sudden control of capital flows.” Since capital flows are the lifeblood of an economy, this indicator highlights the significant role the economy plays in country risk assessments. Gaillard suggests that, regarding capital flows, „the equivocal relationship between economic growth and the liberalization of capital and current accounts should encourage country risk raters to implement analyses of a more qualitative nature when assessing the likelihood that a government will impose restrictions on capital flows.”

Temizsoy and Montes-Rojas (2019) find a positive relationship between risk aversion and the sovereign bond CDS market. With the exception of Greece, they found that „an increase in the ECB refinancing rate or a decrease in money aggregates (M3) increases the risk of government bonds of all countries, except Greece, which has the opposite effect."

In general, many country risk managers continue to examine a country's balance of payments history to determine its economic situation. Bouchet et al. (2018) notes, „From a country risk perspective, assessing the full amount of a country's external debt is both crucial and puzzling. The level of external debt, its evolution, and its composition (that is, its structure of maturity, creditors, debtors, currency, interest rate, and securities vs. loans) are important elements in assessing a country's liquidity and solvency weaknesses, including for cross-country comparisons." It is evident that countries with a substantial amount of debt typically receive a higher country risk evaluation in nearly every model. While international relief programs from the IMF and World Bank can stimulate economic growth, they also contribute to improved country risk ratings.

Governments often intervene in the economy to enhance their country's overall economic situation. These interventions introduce country risk not only in developing nations but also in developed ones. Bouchet et al. (2018) illustrates this point with quantitative easing programs: „Quantitative easing programs can also be considered a source of country risk if they are not implemented in a careful and cautious manner, including their onset and the wind-down. Such unconventional monetary policies impact not only the countries that undertake them but also the economies of entire regions and potentially the global financial system. There is an argument that they can actually increase the frequency and magnitude of financial events with global impact. Large liquidity injections by central banks can create asset price bubbles in the stock and bond markets, while low-interest rates drive investors to seek higher yields in riskier assets, including those in developing countries with weaker institutional and regulatory frameworks. A second wave of risks can emerge when central banks decide to reduce bond buying and scale back quantitative easing. The withdrawal of monetary stimulus can trigger significant capital outflows from developing countries, while rising rates can harm debtors' solvency. The ECB initiated the process to unwind five years of unconventional monetary policy at the beginning of 2018 by deciding to halve its bond-buying programs to facilitate a return to normalcy."

Many of these inventions have country risk aspects. Additionally, actions taken by independent government bodies, such as central banks, can lead to significant problems for a country's economy. The process of globalization was founded on the hegemonic position of the United States, which played a crucial role in the establishment of GATT, the WTO, and other international trade organizations. The development of free liberal global markets was backed by neoliberal think tanks, such as the Heritage Foundation and the Fraser Institute, which continue to advocate for these principles today. However, country risk managers recognize that the emergence of a multipolar world has altered the economic landscape. China and Russia are forging their own economic partnerships, distancing themselves from Western-dominated collaborations, which now must be reviewed for market access. Furthermore, as trade relations between countries evolve, traditional threats to multinational corporations, such as protectionism, are resurging. Gaillard (2020) identifies these threats as follows: „bailouts; state aid; competitive devaluation; consumption subsidies; export incentives; import bans, quotas, and tariffs; intellectual property protection; expropriation; restrictions on investment; localization requirements; 'national content' preferences; sanitary and phytosanitary rules; technical barriers to trade; funding facilities; trade defense measures; and immigration restrictions." Recent discussions at the World Economic Forum (2024) have also addressed this development.

3.2.3 Societal

Companies are facing an increasingly high level of public scrutiny, both domestically and internationally. The rationale behind this scrutiny is clear, encompassing issues such as inequality, ecological concerns, political affiliations, and various claims of misconduct made by the public or media against corporations in every Western society. Kennedy (1987) pointed out the growing recognition of social risk within country risk models used by banks, emphasizing that sociopolitical factors have taken precedence over macroeconomic considerations. There has been a rise in public awareness regarding protests against a company's business operations. New formats of investigative journalism have emerged, contributing to the increased likelihood of multinational corporations becoming targets of public unrest. Social media has made protest efforts against corporations more successful and visible. These efforts are prompting swift responses from both the media and the general population. Societal perceptions of a corporation are crucial to country risk, as they can lead to significant political and financial risks in the current landscape. In this context, political risk related to social risks refers to how protests may influence lawmakers to modify laws or regulations affecting corporate operations. Boycott pledges can spread through social media, reaching a diverse array of potential consumers.

The most pressing and contentious issue is the perception that companies are linked to unsustainable business practices or political extremes, leading to political pressure through public protests and resulting in financial institutions withdrawing their support. This scenario has historically been depicted in the oil and gas sector. Currently, any corporation that generates emissions during its operations may become a target, as shown by Google and Amazon. In the USA, people view both companies as politically progressive entities that advocate for environmental protection, but they also face criticism for their emissions and employment practices. Additionally, a classic issue is the political affiliation of multinational corporations. In the Western context, firms often face challenges in supporting or aligning with political parties. In the recent American election, Elon Musk explicitly endorsed Donald Trump. His most recognized company, Tesla, has been associated with the progressive left in the USA, as electric vehicle production is considered a progressive issue in environmental conservation. His new connection to Trump's right-wing Make America Great Again movement led to public calls for boycotts of the company's products. Another recent example is Budweiser, which illustrates social protest within the U.S. market. An unlicensed advertisement featuring a transgender woman sparked outrage among American conservatives, significantly affecting Budweiser's consumer base. Consumers publicly committed to boycotting the company's products. In both cases, the social media protests were significant, raising concerns among analysts about the potential detrimental impact on the companies. In these examples, it did not matter whether the protests originated from the political right or left.

3.2.4 Environmental

One risk element that varies significantly in nature is ecological threats. Currently, the risks are interwoven across social, economic, legal, and political dimensions. However, since the impending global battle will revolve around commodities, with significant environmental repercussions stemming from mining, agriculture, and other commodity production activities, the risk will increase. For multinational corporations engaged in commodity exploration or associated with it, the present situation signifies an increasing danger of expropriation, adverse legislation, and political opposition.

Environmental organizations are scrutinizing all facets of multinational corporations' supply chains, indicating that manufacturing in the home country may also be influenced by activist initiatives. Multinational corporations that heavily rely on foreign commodities and are perceived to have a negative public attitude regarding exploration activities in other nations are likely to become targets of protest. Moreover, political groups may leverage ecological effects to publicly denigrate enterprises they deem antagonistic to environmental protection. The complexity of the subject, despite the clarity of the scientific consensus, was once again highlighted at the World Climate Conference in Baku in November 2024. The meeting concluded with minimal progress, and the outcome given was condemned for its inadequacy. The inability of countries to reach an agreement stems from various significant country risk issues, encompassing both financial and economic factors. OPEC nations, especially Saudi Arabia, continue to depend on fossil fuels to meet their national development goals, with the intention of completing large urbanization projects and creating a sustainable economy before they transition away from oil and gas exploration and production activities. Moreover, developing nations anticipate financial assistance from the industrialized world to achieve climate objectives. Prolonged fossil fuel consumption and unrestricted carbon emissions yield subsequent benefits. Developing countries and their economies thus require financial support from the global community. Gaillard (2020) concludes that climate change represents the most significant risk, noting that securing financial support for developing countries is challenging due to geopolitical tensions among world powers. His assertion that country risk managers should view climate risk—as part of the broader environmental variable—as a „matrix of all other risks" is compelling. However, his appeal for world policymakers to „coordinate their efforts" should be regarded as a moral request from a country risk manager rather than a feasible expectation for future developments. The frequently cited issue of resource scarcity, alongside the geopolitical ambitions of nations, is likely to create a more complex environment for multinational corporations.

3.2.5 Energy

The model regards energy as a distinct variable, separate from economic or governmental variables, despite their strong correlation. This trend is attributable to the significant role energy will have in the future of nations and corporations. While the Western political sphere endeavors to transition to renewable energy, developing nations are seeking to secure additional oil and gas resources. Energy issues are impacting other factors inside the model, including governance and economics, and perhaps leading to societal unrest, thereby affecting the social variable. As the model does not constitute a standard regression analysis, multicollinearity is not a significant factor in this context. Websites related to energy can provide significant insights into a country's economic and political conditions by disseminating news about the energy landscape of nations.

The impact of energy on a nation was recently evident in Germany at the onset of the Ukraine–Russian conflict. Germany augmented the procurement of Russian gas during the past decade to ensure economical energy for its domestic sector. Following the onset of the war, the European Union initiated sanctions against Russia to exert pressure on the nation. Germany managed to enforce the sanctions; yet, it faced challenges in securing adequate energy for its industry. Germany sought a new energy provider and looked to Qatar for the provision of LNG gas. A contract was criticized due to the human rights situation in Qatar and for regressive negotiations aimed at securing fossil fuels, which many perceive as a betrayal of Germany's ecological initiatives. The evolution of the global energy sector will be crucial and unpredictable in the imminent future. As OPEC exerts greater influence over the oil and gas sector and Western financial institutions seek to diminish funding for fossil fuel operations, the supply dynamics of the energy markets will undergo a transformation. Augmenting investment in nuclear energy and other developments will generate political risk on a worldwide scale. Consequently, energy is likely to assume an increasingly significant role in country risk assessment. Recent research by Li et al. (2021) confirms the role of geopolitics in energy trade, which is part of the energy variable.

3.2.6 Legal

Management must assess the legal climate of its host country before making any investment decisions. Both micro and macro considerations related to legal issues must be addressed. Legislation can become a focal point in international politics and economics. Management must know how enforceable contracts are in the host nation and the duration of court procedures in that country. Multinational corporations must also evaluate the stability provided by international trade organizations, such as the World Trade Organization, within the country. The World Trade Organization is often criticized by global political activists for being a Western institution that aims to maintain the economic supremacy of Western nations, particularly the United States. Consequently, the effectiveness of its guidelines varies, especially in the developing world. Many multinational corporations, therefore, seek to protect their investments through private arbitration courts. The existence of private arbitration courts, which operate independently of any national legal system, raises concerns about their authority to terminate a company's operations and, thus, introduces additional political risk.

Governance can be employed to safeguard multinational corporations from hostile actions taken by foreign governments. Gaillard (2020) provides several examples in which the U.S. government utilizes specific domestic laws concerning aid, foreign investments, and trade to apply pressure on foreign governments that act aggressively toward their MNCs. However, for a nation to effectively use these laws as a defense mechanism, it must possess substantial economic and geopolitical power. Over the past century, with the exception of the United States, few countries have been able to defend their MNCs in this way.

3.2.7 Security

Assessing the security situation within a host country has become increasingly complicated over the years. While the business sector in which a multinational corporation operates is certainly relevant to the level of risk, any MNC can be adversely affected by security developments that deteriorate the overall security landscape in a host country. Terrorist activities, organized crime, and cybersecurity threats are becoming more complex and global in nature. Coupled with instability in many developing countries and shifting global power dynamics, security assessments must be more sophisticated and treated with greater significance.

Civil unrest and terrorism pose direct threats to MNCs by physically damaging their properties. Additionally, MNCs face risks to their supply chains due to disruptions in logistics routes. A frequently cited in-country risk is the Iranian Revolution, which unexpectedly impacted U.S.-based MNCs. In traditional risk models, this risk is often categorized under variables such as revolution or expropriation. However, it is important to note that a full-blown revolution is not necessary for an MNC to be affected by security incidents. Even minor conflicts and terrorist acts can influence financial and commodity markets, as well as government policies. These developments can also be represented in a model addressing socio-political changes (Kennedy, 1987).

Recently, the escalation between Israel and Iran, which began on Friday the 13th, June 2025, has once again subjected the oil market to potential price increases (Kern, 2025). For energyintensive industries, these price spikes have significant effects on production and distribution. Such fluctuations in energy markets have unsettled investors and resulted in rapid and intense capital movements. Moreover, Iran has the capability to block a critical route for oil trade through the Strait of Hormuz, which could lead to yet another surge in oil prices, as twenty percent of global oil exports transit through this narrow passage. The broader implications of this conflict remain to be fully understood, especially following the U.S.'s direct intervention on June 21, 2025. Developments in security within the Middle East serve as a prime example, particularly since October 7, 2023, when a series of events triggered a rapid escalation of multiple conflicts in the region. Alyatama (2016) studied the political risk perceptions of managers in Kuwait during the Arab Spring, providing insights into political risk perceptions within the country and, by extension, the broader region.

Terrorist incidents and armed conflicts have impacted the insurance industry. As previously mentioned, the exposure of multinational corporations to political developments in host countries has created a demand for political insurance, as standard insurance contracts typically do not cover wars and terrorist incidents. According to the Intelligent Insurer (2025), the market for credit and political risk is projected to be worth $49 billion in 2025. Hamdani et al. (2005) from the Federal Reserve Bank of New York analyzed the Political Risk Insurance market from 2003 onward, defining PRI as „protection against losses that result from acts of currency transfer restrictions, expropriation, and political violence.” Offered by national, multilateral, and private insurers, PRI is utilized by investors to mitigate country risks associated with emerging market debt, equity investments, and lending. For insurers, PRI represents a high-cost but profitable business. They characterized PRI contracts as generally ranging from 3 to 20 years in duration, with most contracts skewed towards the shorter end of that range. The report highlights the PRI market as a lucrative opportunity for insurance providers. Research has shown that the influence of domestic institutions on multinational corporations’ risk premiums for PRI depends on the host country’s economic situation; during periods of stable economic performance, political and democratic constraints help protect foreign investors, but in times of financial crisis these protections weaken and the incentives for governments to exploit MNCs increase (Jensen, 2005).

Additionally, the report analyzes cost factors: „The cost of PRI reflects several factors. One important consideration is the unpredictability of losses. The infrequency and uniqueness of political events lead to a lack of reliable data and readily available statistical models for actuarial estimations of future losses.” This criticism underscores the deficiencies in country risk methodologies and the skepticism of risk insurance providers regarding their efficacy, despite ongoing efforts to enhance risk models. The report also identifies the high cost of data analysis in the underwriting process as another factor influencing expenses for insurers. This suggests that even multimillion-dollar insurance companies struggle with the costly data collection necessary for assessing country or political risk, which presents a challenge for multinational corporations attempting to evaluate risk independently without significant resources. Nevertheless, the report indicates that only a small fraction of investments in host countries—specifically in developing or emerging markets—are covered by PRI. Energy projects in these regions may surpass the coverage limits provided by PRI.

Another challenge with Political Risk Insurance is the difficulty in drafting contracts that describe covered events with enough specificity for clear identification while maintaining sufficient generality to avoid overly narrow or cumbersome agreements. A frequent source of litigation in insurance arises from disputes over whether a covered event has actually occurred, as determining the occurrence is inherently subjective. These disputes can create investor concerns regarding insurers' willingness to pay and may frustrate insurers, who feel that investors do not fully grasp the coverage provided. This situation contributes to a pessimistic outlook for PRI. There will always be a certain level of uncertainty and risk of litigation; it is fundamentally impossible to anticipate and describe all potential manifestations of country risk without crafting overly specific contracts and unwieldy. Furthermore, many market participants express skepticism that the existing gaps in PRI coverage can be filled with comprehensive policies that are priced appropriately for buyers who already view PRI as expensive. Consequently, PRI alone cannot be relied upon to replace the essential economic, political, and legal reforms needed to attract foreign direct investment in emerging markets. Nonetheless, the current size of the PRI and credit insurance market underscores the necessity for PRI contracts. Additionally, insurance companies not directly involved in political insurance can also be affected by security incidents. For instance, following the events of September 11, 2001, the stock values of US-based insurance companies plummeted, and this correlation has been observed repeatedly since then. Political risk protection typically focuses on specific, sudden hazards, such as nationalization, capital controls, confiscation, kidnapping, and terrorism (Bouchet et al., 2018). Coface, for instants, offers insurance policies that are tailored for complex, long-term projects and cover non-payment risks stemming from political events (Coface, 2025). This feature highlights the importance of country risk assessment as a key business aspect for specialized insurance companies.

A more modern threat is cybercrime, which multinational corporations face when their systems are compromised by various forms of hacking, extortion, espionage, data manipulation, and deletion. MNCs must maintain high connectivity between facilities, resulting in numerous potential points of attack. Even the most robust cybersecurity defenses can be undermined by human error. Assessing cyberthreats in the context of country risk is challenging. While some countries, such as China, Russia, and North Korea, are known for targeted attacks on MNCs, the overall threat remains opaque and difficult to incorporate into a country risk model. For instance, a US-based company's operations in Ghana could be targeted by a Russian hacker group using servers located elsewhere in the Americas, making it impossible to link the threat directly to Ghana. The only viable quantitative and qualitative assessment of cyberattack risks for MNCs in Ghana is to retrospectively analyze past cyber incidents within the country. Another cybersecurity threat involves artificially manipulated news and videos; AI tools are increasingly adept at creating propaganda and false narratives that can incite violence and unrest.

The security situation globally over the next decade will also be influenced by resource depletion, as mentioned in the introduction. While oil is the most recognized strategic commodity considered by nations, modern societies depend on a wide range of commodities to maintain stability. Terrorist groups and religious extremists may exploit scarcity, particularly in nations rich in natural resources, to disseminate propaganda and incite uprisings and violence worldwide. Currently, the United States views China's dominant position in the rare earth elements sector as a national security concern, given that these elements play a crucial role in both economic and military applications (Shepherd and Li, 2025). In the future, developing countries will need to recognize more basic commodities, such as water and grains, as national security issues. In African nations, where hunger already contributes to civil unrest, these resources will become increasingly critical for national stability.

When global orders change, such as the increasingly nationalistic behavior of the United States, the dynamics of intervention in conflicts involving developing countries also shift. Bouchet et al. (2018) referred to this change as the „end of US-dominated multilaterals," a framework that has prevailed since World War II. Additionally, the United Nations, which has recently struggled to act effectively in significant conflicts, will likely be unable to determine a clear course of action. Particularly in Africa, China's expanding global influence is likely to manifest in emerging conflicts. By implementing strategic policies aimed at African nations, China has already established a significant presence on the continent, utilizing these relationships to bolster its military footprint, as seen at the port of Djibouti. Moreover, China is actively working to secure various commodities in Africa through exploration contracts with local governments. The country is also exploring resources in Asia, including in unstable nations like Afghanistan and Iraq, where it now operates the largest oil field. While the global scramble for commodities raises concerns for many governments, it is crucial to recognize that demand for these resources is expected to surge as developing countries strive to narrow the gap with the developed world. Consequently, multinational corporations should consistently consider potential shifts in nationalization policies regarding resources within host countries.

According to Bouchet et al. (2018), investors often perceive developing countries as a single asset class and are concerned about spillover effects, which can lead to simultaneous withdrawals of investment from multiple nations. This means that security incidents can negatively impact adjacent countries, affecting the financial stability of host countries for multinational corporations. As a result, MNCs may struggle to secure financing for their operations in a host country.

MNCs experience varying levels of exposure to the security situation in a host nation. While financial institutions typically hold liquid investments that can be quickly relocated, industrial MNCs have established production facilities and consumer markets within the host country. Such MNCs risk expropriation during military coups and can also suffer direct damage from violent attacks against their facilities by non-state actors. These non-state actors include not only terrorist groups but also private military companies, which are increasingly expanding their influence and creating heightened threats within host countries (Office of the Director of National Intelligence, 2024a). MNCs are not merely collateral damage; they often become targets for these non-state actors. Particularly, U.S. companies are considered representatives of the U.S. government and, by extension, become targets for hostile non-state entities. For a long time, MNCs have been viewed as symbols of Western hegemony and, in some instances, as instruments of modern colonization. This perception is especially pronounced when MNCs capture significant market shares in domestic markets, thereby undermining local companies' ability to compete.

Additionally, hostilities from citizens and domestic economic entities can be exploited for political unrest, which can lead to physical attacks against MNCs, making it even more challenging to secure financing for future investments in host countries. Furthermore, companies in certain industries, such as oil, are often associated with environmental damage, exposing them to increased risks.

4. EMPIRICAL ANALYSIS AND DISCUSSION

4.1 Sentiment Analysis

Sentiment analysis is the initial step in analyzing the collected data. The sentiments are categorized into three labels: positive, negative, and objective. To perform sentiment analysis, the text input must undergo tokenization. Tokenization is the process of converting words into unique numerical identifiers. Python libraries assist in converting the text inputs stored in the MySQL table into these unique identifiers. Since the sentiment dictionary is in English, the input data is pre-assessed for language. Any non-English input is translated prior to analysis by sending it via an API call to OpenAI for translation. This procedure ensures that the data is compatible with the appropriate sentiment packages. Before tokenization occurs, the data is cleansed of punctuation, HTML code, and other unwanted elements that could distort the sentiment analysis. Each input text is assigned a unique ID for identification purposes. In the subsequent 3D scatterplot, each input text can be identified by its corresponding ID number. The dictionary utilized is SentiWordNet, which is available on GitHub for conducting text analysis. As described on GitHub, SentiWordNet is a lexical resource for opinion mining, assigning three sentiment scores—positivity, negativity, and objectivity—to each synset of WordNet. Consequently, it serves as a lexicon-based method for sentiment analysis, providing sentiment scores for individual words.

4.2 The Neural Network for the Country Risk Model

The concept of employing neural networks in country risk assessment is to manage the extensive volume of available open-source intelligence data, which exceeds the capacity of any single individual if a daily assessment is required, as well as to process daily data quantities that even management teams cannot effectively handle. As machine learning and artificial intelligence research advances, it is essential to include these developments in country risk assessment modeling. This approach is also predicated on the incorporation of new methodologies for gathering data pertinent to country risk assessment. A substantial quantity of pertinent data resides on news websites, in blog posts, within insider columns, in background stories, and in governmental declarations. A comprehensive and continuously monitored database must be established for country risk assessment.

Supervised and unsupervised neural networks can assist in the evaluation. The model design depends on the achievements the neural network aims for, as well as the structure of the data the model is receiving as an input (Gale, 2024). The news data on the World Wide Web is frequently accessible without barriers; at times, data is even provided pre-sorted with API access (see ALEG). Additional input, classified as open-source intelligence data, can be provided by paid subscription. This, however, was excluded from this research due to its limitations in regard to financing. Nonetheless, as it is classified as open-source intelligence, any additional input would significantly expand the database. This thesis involved the daily scraping of several hundred websites for data via Changedetection. Evaluating the data input is a critical consideration for every country risk model, regardless of whether it involves questionnaire data, regression variable model data, or the data used in this neural network. The objective of the neural network is to analyze the data input, which is the result of the sentiment analysis. The neural network analyzes the data and generates a positive or negative trend forecast regarding country risk (as outlined in 8.3 (Code Appendix)). The sentiment analysis and neural network allow for the selection and individual analysis of factors and countries.

The research aimed to produce a model by establishing an individual database that was unattainable during Robock's day. Any substantial output from a model necessitates the collection and storage of requisite data in adequate quantities for analysis. An external service is utilized for collection reasons, which hosts the open-source software Changedetection. Changedetection is a fundamental component of the infrastructure, facilitating data collection and transmission to the server via an API POST statement. Changedetection observes third-party websites for modifications by utilizing the CSS framework of a site and transmits the altered data to a designated address. This research required a private server, which then stored the transmitted data in a MySQL database (as outlined in Figure 4 below).

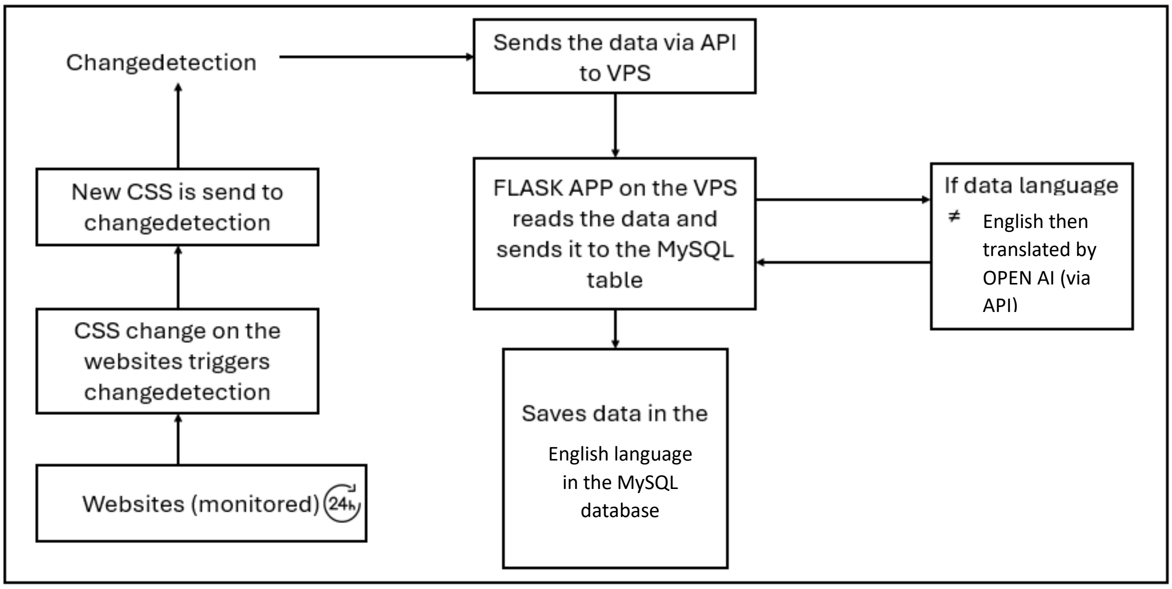

Figure 4. Changedetection *Source*: Author

At the outset of every model, the issue of data refinement arises. When Changedetection monitors a website, the visual filter tool assists in selecting the precise CSS portions of the site. Nevertheless, the websites are frequently constructed in a manner that prevents the program from extracting individual words or numbers. This indicates that the data cannot be refined prior to its utilization in the neural network study. In contrast to the stringent refinement required for quantitative methods such as regression analysis, the qualitative data approach utilizing a neural network is presumed to be more adaptable, provided the data input is sufficiently extensive. Datasets capable of substantial scaling should maintain minimal volatility due to extensive data input.

ID	INSERT_TIME	WEBPAGE	COUNTRY	VARIABLE	NEW_DATA_TRANSLATED	NEW_DATA
19676	20.02.2025 00:13	https://citinewsroom.com/tag/strike/	GHA	soc		* About Us * Contact Us * Photo
19677	20.02.2025 00:13	https://www.pulse.com.gh/search-results?keywords=	GHA	soc		Loading
19678	20.02.2025 00:16	https://www.gbcghanaonline.com/?s=strike	GHA	soc		Government questions legal basis of CLOGSAG's pla
19679	20.02.2025 00:18	https://www.gbcghanaonline.com/?s=protest	GHA	soc		Obuoho youth protest unlawful burning of excavato
19680	20.02.2025 00:25	https://animalpolitico.com/sociedad	MEX	soc	Read later Banxico cuts its growth forecast for Mexic	Leer después Banxico recorta a 0.6 % su pronó
19681	20.02.2025 00:26	https://www.milenio.com/temas/manifestaciones	MEX	soc	* 18.02.2025 March in the center of Monterrey for ma	* 18.02.2025 Marchan en el centro de Monterrey pc
19682	20.02.2025 00:28	https://edition.cnn.com/world/americas/mexico	MEX	soc		â¢ Live Updates Live Updates Jim Watsoı
19683	20.02.2025 00:32	https://blueprint.ng/?s=energy	NGA	ene		Business NIES 2025: Omogiafo to deliver keynote a
19684	20.02.2025 00:34	https://www.environewsnigeria.com/category/energy/	NGA	ene		Renewable Energy Ethiopia signs MoU with A
19685	20.02.2025 00:35	https://www.premiumtimesng.com/search_gcse?q=NI	NGA	ene		Custom Search
19686	20.02.2025 00:39	https://www.vanguardngr.com/search/energy	NGA	ene		Experts demand urgent action on Nigeria's energy c
19687	20.02.2025 00:40	https://mexiconewsdaily.com/category/news/	MEX	soc		2025 Future of Mexico Forum: MND interviews Valeri
19688	20.02.2025 00:40	https://www.vanguardngr.com/search/oil	NGA	ene		Nigeria's oil output excluding condensate rises by 4
19689	20.02.2025 00:42	https://punchng.com/tags/NMDPRA/	NGA	ene		Latest News * 17th February 2025 NMDI
19690	20.02.2025 00:44	https://thenationonlineng.net/tag/NMDPRA/	NGA	ene		NMDPRA NMDPRA bans over 60,000ml petrol truc
19691	20.02.2025 00:44	https://businessday.ng/category/energy/	NGA	ene		* Home * > * Energy Energy Petrol import pe
19692	20.02.2025 00:45	https://politica.expansion.mx/sociedad?utm_source=	MEX	soc	Society What courses does the CECART training cent	Sociedad * Sociedad ¿Qué cursos ofrec
19693	20.02.2025 00:51	https://leadership.ng/tag/renewable-energy/	NGA	ene		Tag: Renewable Energy Reps To Hold Summi
19694	20.02.2025 00:53	https://www.ripplesnigeria.com/tag/dangote/	NGA	ene		* Business 2 days ago Dangote on $23bn refine
19695	20.02.2025 01:00	https://www.promexicoindustry.com/en/news	MEX	soc		San Luis Potosí February 2025 San Lı
19696	20.02.2025 01:01	https://www.csis.org/	GLO	sec		Image Mining for Defense: Unlocking the Poten
19697	20.02.2025 01:02	https://intelnews.org/	GLO	sec		Review of "Chinese Espionage Operations and Tacti
19698	20.02.2025 01:05	https://thenationonlineng.net/business/	NGA	eco		Business Academy launches initiative to end Nig
19699	20.02.2025 01:05	https://punchng.com/topics/business/	NGA	eco		Latest News * 20th February 2025 Vehic
19700	20.02.2025 01:06	https://www.premiumtimesng.com/category/business	NGA	eco		More News FG plans to ban overloaded petr
19701	20.02.2025 01:07	https://tradingeconomics.com/nigeria/news	NGA	eco		* Nigeria Inflation Rate Falls to 24.48% After Data
19702	20.02.2025 01:09	https://businessday.ng/tag/bdlead/	NGA	eco		BDlead Health workers unemployment soars to 26
19703	20.02.2025 01:09	https://www.vanguardngr.com/category/business/	NGA	eco		Austriacard to partner banks, fintechs, others boost
19704	20.02.2025 01:12	https://businessday.ng/category/business-economy/	NGA	eco		Economy CBN to boost remittances from Nigerian
19705	20.02.2025 01:13	https://businessday.ng/category/companies/	NGA	eco		Companies Dangote to double its Ethiopia cemen
19706	20.02.2025 01:13	https://businessday.ng/category/markets/	NGA	eco		Markets Here're analysts views on stocks ahead o

Figure 5. Illustration of the MySQL table *Source*: Author

The private server is equipped with a Python *listener* script that facilitates API access. The foundational FLASK library is capable of executing the necessary actions (API connection) to gather data from specific websites and transmit it to a private server.

When the *listener* script processes a POST command, it reads the transmitted data and converts it for storage in a MySQL table. The *listener* has been manually initiated on the server for the first time and is secured with an auto-run command. It utilizes FLASK application technology for its functionality. The data is contained within a JSON string, and the *listener* script can categorize this data by specified country and variable using a group tag for labeling (for example, 'GHA_sec' would be categorized as Ghana and security).

Moreover, the *listener* script can determine the language of the transmitted data through the Python library langdetect. If it's not detected as English, it is sent for translation to OpenAI via API. It channels the input data into specific MySQL columns: ID, TIMESTAMP, OLD DATA, COUNTRY, VARIABLE, and LANGUAGE. The private server supports a MySQL database with columns that include ID, TIMESTAMP, WEBSITE, OLD DATA, NEW DATA, NEW DATA TRANSLATED, VARIABLE, LANGUAGE, and COUNTRY. The MySQL Workbench tool is used to access stored data and create appropriately labeled tables for retrieval by R Studio (as outlined in Figure 5 above).

Changedetection allows for the integration of an API within the notification section, which facilitates the sending of data to the *listener* script on the server. The API connection comprises the server's IP address and directives for which website updates should be transmitted to the *listener*. The *listener* is invoked using the POST command of the protocol language employed for the API of Changedetection. MySQL stores the data, which can be accessed by R Studio for subsequent analysis (as outlined in Figure 6 below). RStudio is an environment for the statistical programming language R. It includes a package-based environment for different statistical and mathematical analyses. The package encompasses methods employed for country risk assessment. Moreover, virtual environments can utilize Python language packages. The packages TensorFlow and Keras are required here. These packages include the possibility of neural network analysis, along with the element of unsupervised learning.

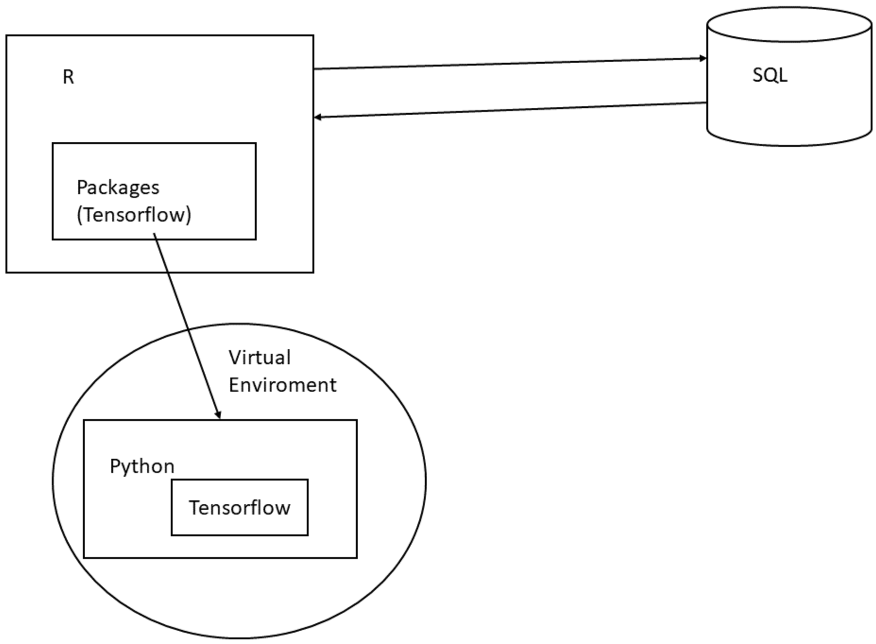

Figure 6. Tensorflow in a virtual environment *Source*: Author

To create the neural network model planned for this research, the application TensorFlow utilizes multiple related machine learning packages. (Carter, 2024) TensorFlow, developed by a team of Google engineers, is a sophisticated program for building neural networks. It incorporates the program Keira, which serves as a standard tool in machine learning and neural network applications. Because TensorFlow is a Python-based program, it is necessary, in addition to installing Python, to create a virtual environment for use in RStudio. One must install TensorFlow again within this virtual environment. Subsequently, additional packages are installed in R Studio to link it to the Python virtual environment, enabling the design and execution of the neural network within R Studio (as outlined in Appendix 8.3). R as a language and RStudio as the Integrated Developer Environment (IDE) are suitable to handle neural networks. (Ciaburro and Venkateswaran, 2017) The deep neural network operates with non-linear data, allowing for the inclusion of variables in the same model that might not exhibit significant regression in a linear regression model.

The input consists of vectors constructed from positive, negative, and objective classifications. The deep neural network is capable of learning from clusters and uncovering hidden relationships within the data using these classifications, indicating its self-learning capability. Moreover, the network is designed to handle complex and large datasets efficiently. At present, the input size includes data from 808 websites, which undergo daily monitoring. While not every website provides daily updates, the majority do, allowing for rapid scaling of the dataset. This dataset is highly scalable, with entry rows potentially exceeding several hundred to a few thousand data entries. Additionally, the complexity of the data arises from its text-based nature. Managing this complexity requires careful monitoring of computational resources and ensuring their availability. R Studio can perform intricate calculations on standard computers, but as the model evolves, there will be a need to extend computational power.

The deep neural network has the advantage of analyzing non-linear relationships that are inherently present in country risk data. It can process sentiment analysis data along with the constructed vectors to conduct trend analysis. The sigmoid activation function in the last layer neuron allows for a binary output, indicating either a positive or negative trend. Additionally, the deep neural network can be expanded by adding more layers and neurons. (Aggarwal, 2018). The input data vectors will first pass through the initial layer, which contains 128 neurons. A ReLU activation function determines whether the data will proceed to the subsequent layers. The second, third, and fourth layers also utilize the ReLU function for activation. The second layer contains 128 neurons, the third layer has 64 neurons, and the fourth layer comprises 32 neurons. The final layer employs the sigmoid activation function, which uses z-scores for activation, calculated as the sum of the assigned weights. These weights are determined for each input row, underscoring the need for substantial computing power (as outlined in Appendix 8.3).

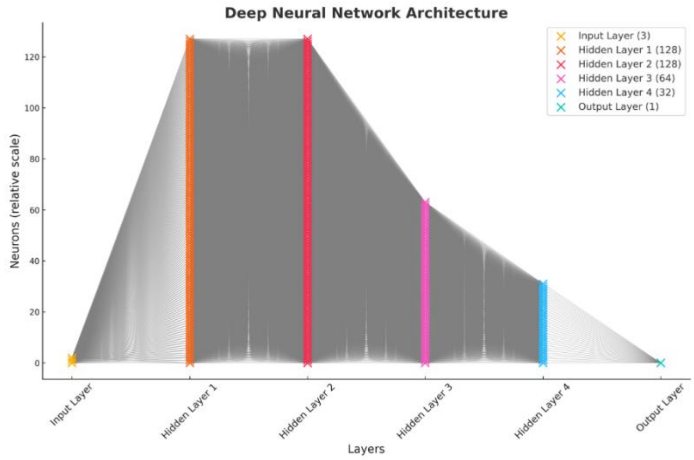

Figure 7. AI created theoretical representation of a 4-layer ANN *Source*: OpenAI

Weight calculation for layer 1-4

$$z = w_1 x_1 + w_2 x_2 + \cdots + w_n x_n + b$$

Weight calculation for the last layer

$$z = w_1 h_1 + w_2 h_2 + \cdots + w_n h_n + b$$

ReLu activation in layer 1-4

$$\mathrm{ReLU}(x) = \max(0, x)$$

For $x > 0$: $\mathrm{ReLU}(x) = x$

For $x \leq 0$: $\mathrm{ReLU}(x) = 0$

Sigmoid activation in the last neuron

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

4.3 K-means Cluster Analysis

After the sentiment analysis, the k-means algorithm examines the data to build clusters. K-means clustering calculates the centroids in the network. The clusters can be calculated for every variable and country individually. The cluster analysis is not necessarily a requirement for the country risk assessment with a neural network, but it can help to identify abnormalities in the network's output. Within this research, the cluster analysis plays a marginalized role and serves mainly for error monitoring (as outlined in Appendix 8.3).

4.4 3D Scatterplot, Timeline and Interface Program

The three-dimensional scatterplot serves as an effective illustration of the concept. It seeks to demonstrate sentiment analysis, cluster formation, and a timeline of net sentiment. This feature provides an overview of the input data and the neural network's results. The model requires a substantial quantity of data to function effectively. The scatterplot hence possesses numerous data entry points and can be overwhelming. Therefore, within the 3D scatterplot, the points have the individual ID entry for identification, as well as the negative, positive, and objective values. Each point additionally illustrates the net-sentiment value and the anticipated neural network trend (as outlined in Appendix 8.3).

4.5 The Results of the Neural Network

H1: A neural network analytical framework can be developed for country risk assessment utilizing individually collected daily open-source intelligence data.

In addition to being fully functional, the code that was written for this thesis is capable of producing significant results for any nation that was chosen to serve as an example for this research. Based on the following data entry, the model makes a prediction regarding whether or not the sentiment associated with a particular variable would increase. Once it has been trained using sequential data, it will produce a binary signal that indicates whether an upward or downward shift in sentiment is anticipated. Due to the fact that the input data was developed to represent a comprehensive country risk model, this change is revealing the country risk that multinational firms face. The model accurately depicts the direction of short-term sentiment progression based on document order, and it does so without being dependent on a predetermined level of time horizon. As a result, H1 indicates a positive outcome.

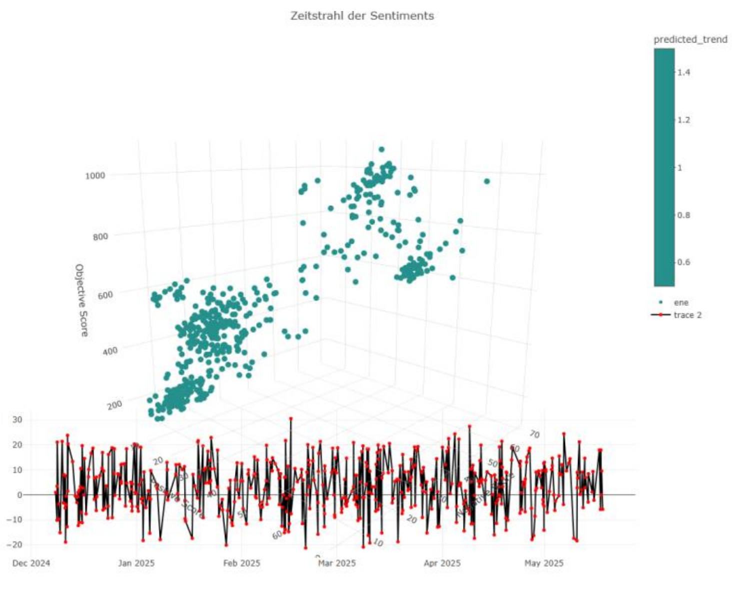

Figure 8. Positive trend prediction Germany May 5th *Source*: Author

The model was tested with a time stop. On the 5th of May 2025, the model made an accurate prediction that Germany will have a positive trend within the government variable. On May 6th 2025, Germany formed its new government, which was an event that was regarded favorably on the international stage. This conclusion was due to the fact that it was regarded as a symbol of stability in Europe and a continuation of Germany's position in terms of its foreign policy.

The anticipated strong election results for the far-right party in Germany posed a threat to this stability.

```
> summary(nn_model)
Model: "sequential"
________________________________________________________________________________
 Layer (type)                       Output Shape                    Param #
================================================================================
 dense_4 (Dense)                    (None, 128)                     512
 dropout_3 (Dropout)                (None, 128)                     0
 dense_3 (Dense)                    (None, 128)                     16512
 dropout_2 (Dropout)                (None, 128)                     0
 dense_2 (Dense)                    (None, 64)                      8256
 dropout_1 (Dropout)                (None, 64)                      0
 dense_1 (Dense)                    (None, 32)                      2080
 dropout (Dropout)                  (None, 32)                      0
 dense (Dense)                      (None, 1)                       33
================================================================================
Total params: 27393 (107.00 KB)
Trainable params: 27393 (107.00 KB)
Non-trainable params: 0 (0.00 Byte)
________________________________________________________________________________
```

Figure 9. Neural Network layout – Nigeria May 11th *Source*: Author

Furthermore, the model also predicted a positive trend for Nigeria in the economy variable on May 11th. On May 12th, the World Bank gave a positive outlook statement for Nigeria's economy.

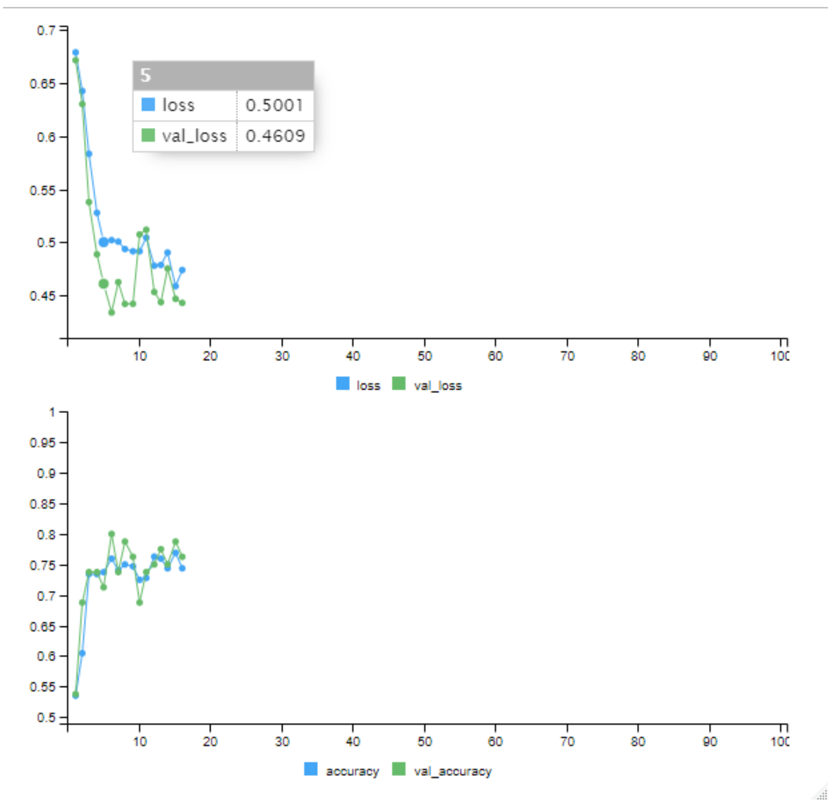

Figure 10. Validation accuracy and validation loss for Mexico March 17th *Source*: Author

In addition, the model performed accurately when it predicted that the government variable for Mexico would have a favorable outlook on March 17th. Claudia Sheinbaum introduced an important legislative act March 18th that reformed Mexico’s energy sector.

H1.1: The proposed neural network demonstrates statistically significant predictive performance, as evidence by model interpretability techniques such as LIME (Local Interpretable Model Agnostic Explanations), SHAP (Shapley Additive Explanations) and the results of a K-fold analysis.

The results of the LIME and SHAP analysis were mixed. While the actual predictions, with the exception of Mexico, were significant, the explanation fit was low. In the case of SHAP, this is also true for the average prediction. The results, however, don't make the model insignificant (as outlined in Table 3 below). The success of the one-day prediction highlights the actual predictions from Germany and Nigeria.

country	LIME	SHAP
Germany	Explanation Fit: 0.54	Actual Prediction: 0.91 Average Prediction: 0.57
Mexico	Explanation Fit: 0.4	Actual Prediction: 0.06 Average Prediction: 0.48
Nigeria	Explanation Fit: 0.43	Actual Prediction: 0.87 Average Prediction: 0.50

Table 3. LIME and SHAP results for the three events examined *Source*: Author

The K-fold analysis shows significant mean accuracy values for a binary prediction. The mean-prediction values are also significant. Overall, the K-fold values show the model as statistically significant (as outlined in Table 4 below). Since the K-fold test results are seen here as superior to the LIME and SHAP results, the H1.1 is seen as positive, and the model gives significant results with the exemplary tests.

country	date (one day prior to event)	event	mean-accuracy	mean-precision	mean-recall	mean-f1-score	mean-auc
Germany	05.05.25	Gov.	0.703	0.711	0.689	0.695	0.780
Mexico	17.03.25	Gov.	0.762	0.794	0.738	0.758	0.859
Nigeria	11.05.25	Eco.	0.7	0.752	0.598	0.656	0.797

Table 4. K-fold analysis of one day ahead event prediction *Source*: Author

H1.2: The model effectively addresses and overcomes the limitations of linear assumptions inherent in traditional quantitative country risk assessment methodologies.

The variables within the databank are for all countries the same. The data is collected over a time span of over half a year, which leads to positive and negative data input in unequal amounts and in irregular time periods. Since the model overcomes the obstacles of H1 and H1.1 and produces a significant working model with the non-linearity problem in hand, H1.2 must be answered positively. A neural network analysis framework based on open-source intelligence data can overcome the non-linearity problem. The one-day-ahead model results show that the model performs stably; however, there remains potential for further fine-tuning. Possible improvements include increasing or decreasing the number of layers within the deep neural network. Furthermore, the learning rate could be increased if necessary, as could the batch size of the input matrices during training. The latter two adjustments, however, would only be advisable if the dataset were to increase considerably in size.

4.6 The Results of the Neural Network -Weekly/Monthly Predictions

Both the weekly and the monthly prediction models used a linear activation function in the final layer, thereby changing the final activation from a sigmoid function to a linear regression. The code used for the weekly and monthly predictions was based on the original code developed for the one-day-ahead prediction but required further adjustments, as shown in Appendices 8.5 and 8.6. These models were trained and evaluated using the same dataset as the one-day-ahead model.

Due to issues related to data density, the most suitable data stream for the model was the country-level data for Mexico, using variables derived from the collected government data. Within this data stream, limitations in data collection became apparent through an increased level of noise, as well as the appearance of warning signs typically associated with a risk of overfitting during training. However, despite these issues, the results indicate that while the mean AUC values are low and require further training, they are sufficiently high to suggest that additional training is promising.

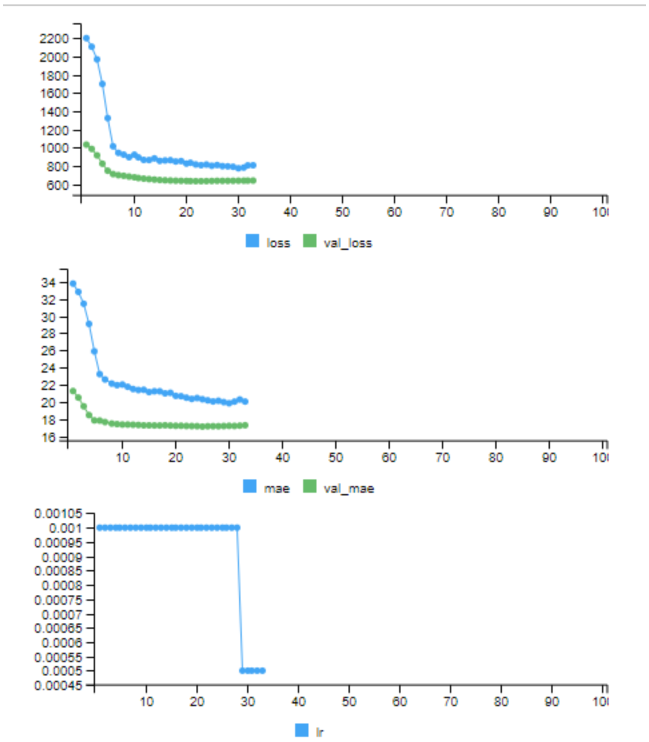

Figure 11. Validation accuracy and validation loss for Mexico (weekly prediction) *Source*: Author

In the weekly prediction using the Mexican government variable, with a start date of December 1st, 2025, the model also exhibited insufficient mean AUC performance. As stated above, Mexico was selected because it provided the densest data collection among all monitored countries. However, the mean absolute error and the loss decreased sharply within the first ten epochs and then remained nearly unchanged, without further convergence. This behavior caused the learning rate to decrease around the 30th epoch to a value below the already low learning rate of 0.001.

The remaining K-fold analysis indicates additional potential issues with the data. Although the OSINT collection component of the model is capable of collecting near-infinite amounts of data within the technical limits of the system, the dataset collected within the constraints of this research was likely insufficient for robust model training.

country	LIME	SHAP
Mexico	Explanation Fit: 0.13	Actual Prediction: 23.03 Average Prediction: 27.11

Table 5. LIME and SHAP results for the weekly prediction *Source*: Author

The SHAP actual prediction values are low, particularly when compared to the results of the one-day-ahead model, whereas the LIME model provides an explanation framework similar to that used for the one-day-ahead prediction. For the weekly and monthly models, K-fold analysis is also employed as the primary method for performance assessment.

The K-fold analysis for the Mexican government variable with a start date of December 1st shows high levels of mean accuracy, mean precision, mean recall, and mean F1-score. However, the previously discussed mean AUC indicates that the model requires further improvement before it can be applied in practice. The rolling mean window was evaluated at lags 3 and 7.

country	stop date	event	mean-accuracy	mean-precision	mean-recall	mean-f1-score	mean-auc
Mexico	01.12.25	Gov.	0.831	0.844	0.982	0.907	0.582

Table 6. K-fold analysis for the weekly prediction *Source*: Author

The monthly prediction also uses December 1st, 2025, as the start date. The monthly prediction applies a 30-day window, thereby representing sentiment predictions for December 2025. Within this period, Mexico exhibited some positive signals, including a reduction in the fiscal deficit in 2025 and the achievement of a water delivery agreement with the United States.

In this case, the rolling mean window was set to 15 and 30.

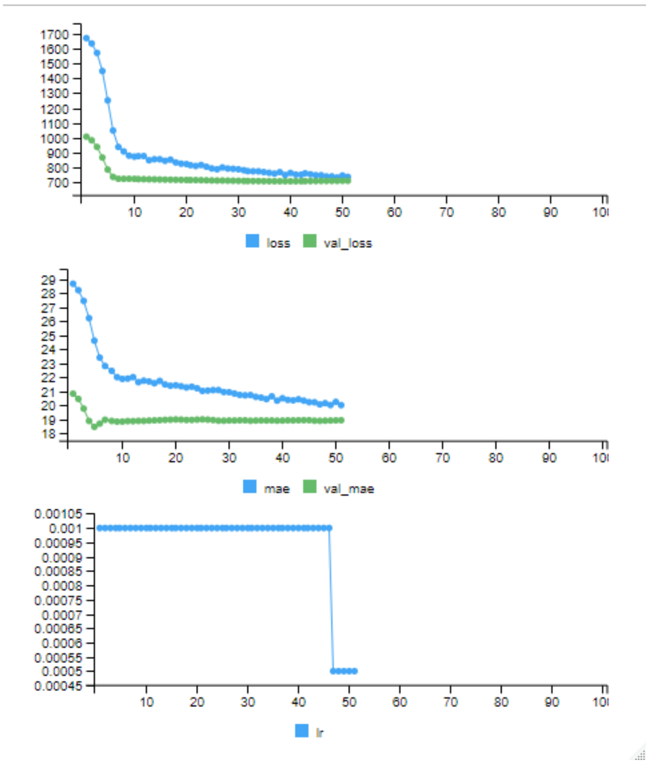

Figure 12. Validation accuracy and validation loss for Mexico (monthly prediction) *Source*: Author

The figure above shows the mean absolute error and the validation loss, as well as the training loss and validation loss, using a learning rate of 0.001. These results indicate that the model is capable of functioning; however, its capacity is likely greater than what the available data can support. Around the 50th epoch, both the loss and the mean absolute error fall below their corresponding validation metrics. In addition, the learning rate decreases around the 45th epoch, which provides a further indication of overfitting when considered alongside the observed behavior of the validation mean absolute error and validation loss.

country	LIME	SHAP
Mexico	Explanation Fit: 0.11	Actual Prediction: 18.43 Average Prediction: 26.36

Table 7. LIME and SHAP results for the monthly prediction *Source*: Author

The monthly prediction values for LIME and SHAP exhibit behavior similar to that observed in the weekly predictions. Again, these results are not considered as important as the K-fold analysis; however, the SHAP values remain extremely low.

country	stop date	event	mean-accuracy	mean-precision	mean-recall	mean-f1-score	mean-auc
Mexico	01.12.25	Gov.	0.836	0.837	1	0.910	0.612

Table 8. K-fold analysis for the monthly prediction *Source*: Author

In addition to the LIME and SHAP values, the K-fold analysis performance presents results indicating that the model exhibits insufficient mean AUC. Mean recall again gives the impression of an overfitting model, likely due to missing data. The monthly-ahead prediction requires a 30-day linear regression and therefore incorporates more data than the weekly prediction. Even though the Mexican government variables provided the best data coverage, the dataset still appears to be too small.

Furthermore, the weekly and monthly prediction capabilities require additional optimization. With a wider database, the model could likely perform more stably. Although the model has collected nearly one hundred thousand data points to date, the predictions remain noisy when using a linear activation function in the final layer. One underlying issue is that certain variables and countries are better covered by news outlets and expert reports than others.

While the LIME and SHAP values were problematic in both the one-day-ahead and the monthly prediction models, the K-fold analysis would most likely improve with more extensive data. In the case of the monthly prediction, the model frequently suffered from too many missing data points to meet the forecasting objective. For such long forecasting horizons, the data collection process must be significantly more extensive.

In general, as with other neural network applications, the model developed in this thesis requires a higher volume of input data to effectively support a linear activation function in the final layer. The model itself cannot influence how frequently news outlets report on specific topics. Therefore, future research must increase the volume of input data in order to enable reliable monthly predictions for all model variables at any point in time. If data inflow remains low, expanding the number of monitored websites could mitigate this limitation and generate sufficient data for analysis and prediction.

H2: The model will perform better in one-day-ahead predictions than in weekly and monthly predictions.

The one-day-ahead model performed better than both the weekly and the monthly prediction models. The mean AUC values obtained from the K-fold analysis showed unsatisfactory results for the weekly and monthly forecasts, indicating that these results must be examined with respect to potential overfitting. Furthermore, the recall and F1-score values are excessively high, and the high prediction accuracy is likely influenced by noisy and missing data points.

The sigmoid activation function performed better with the data collected through the model's OSINT collection process than the linear activation function used in the weekly and monthly prediction models. The one-day-ahead prediction model appears to be more capable of mitigating data noise. Overall, the K-fold analysis also demonstrates more conclusive performance for the one-day-ahead prediction.

Although the mean AUC and prediction results are not optimal, they provide sufficient positive feedback to justify using the model in its current form while monitoring future results to identify potential areas for fine-tuning. In contrast, the weekly and monthly prediction models clearly indicate a need for increased data availability. Therefore, Hypothesis H2 is confirmed.

4.7 Comparison of Country Risk Rating

There are challenges in comparing the results of this thesis model with other country risk models. The models used by institutional country risk assessment firms are proprietary, and even academic attempts to replicate them never yield results that are exactly the same as those produced by the institutions. A primary issue in this research is the varying time horizons across different studies. The data collected for this thesis is primarily daily, whereas established models typically utilize longer time frames. Additionally, the time horizon of the model developed in this research is not fixed to a specific period. Although it has been tested for one-day-ahead predictions, it has not been specifically trained for this purpose. The goal of this approach is to improve the model's adaptability, enabling it to undergo training at a later date for specific time periods.

Nonetheless, one can compare the overall trend predictions of country risk from this model to the most recent institutional risk assessments. The following section presents a comparison of their ratings for the five countries analyzed. For Mexico, Vietnam, and Germany, the trend predictions align closely with institutional rankings (as outlined in Table 9 below). Ghana also fits within the institutional framework, although not as clearly as the other countries. The positive trend prediction for Nigeria stands out, as it sharply contrasts with institutional assessments. This discrepancy is likely due to the recent collection of positive sentiment data that influenced the model, which may not yet have been incorporated into the assessments of other models.

Model	Mexico	Vietnam	Germany	Nigeria	Ghana
Coface	B	A4	A3	C	C
OECD CRC	3	5	1	6	6
Fitch Solutions	72	71	81	46.6	53.1
Economist Intelligence Unit (EIU)	70-75	71	83-85	50-60	54-60
Thesis model	0 (negative)	1 (positive)	1 (positive)	1 (positive)	0 (negative)

Table 9. Comparison to other Country Risk Ratings *Source*: Author

4.8 Individual Variable prediction

The variables represent distinct facets of country risk, and each must be capable of producing a valid result independently. This step is especially important if a multinational corporation identifies a particular variable that poses a greater risk to its operations. While the overall country risk trend requires that the variables be equally weighted in terms of the websites monitored, an MNC might later focus on just one variable and increase the data input for that specific area. This decision would largely depend on the nature of the MNC's business. For example, a production company with limited political exposure might be more concerned with energy stability, prompting it to enhance the data input for that variable.

In this research, it is ensured that the variables were equally weighted regarding the websites monitored to maintain universality. The model successfully generated a trend for each variable. However, some variables accumulated more data over time than others, as news coverage varies by topic. The most effective data collection occurred for the variables related to government and economy. The utilized events from these variables assess the significance of the results and to evaluate the significance of the trend predictions.

Variable	Mexico	Vietnam	Nigeria	Ghana	Germany
Energy	1 (positive)	0 (negative)	1 (positive)	1 (positive)	1 (positive)
Environment	0 (negative)	1 (positive)	1 (positive)	1 (positive)	1 (positive)
Economic	0 (negative)	0 (negative)	0 (negative)	0 (negative)	1 (positive)
Government	0 (negative)	1 (positive)	1 (positive)	0 (negative)	0 (negative)
Security	0 (negative)	0 (negative)	1 (positive)	0 (negative)	1 (positive)
Legal	0 (negative)	1 (positive)	1 (positive)	0 (negative)	0 (negative)
Social	0 (negative)	1 (positive)	1 (positive)	0 (negative)	1 (positive)

Table 10. Individual results of the thesis model variables *Source*: Author

4.9 Discussion

The thesis model can be optimized and requires ongoing monitoring of data input throughout its lifespan; nevertheless, it also presents opportunities for further research. The initial study objectives should focus on advancing the model for every country acknowledged by the United Nations, assessing if the infrastructure can accommodate the data volume and generate significant results. The second potential area of ongoing research may be the dimensions of the concealed relationship that the model does not show. The issues addressed with constraints within the model indicated that, despite the fact a deep neural network may discern concealed patterns, it lacks the capacity of a political strategist to perceive the political nuances that affect certain political processes, irrespective of sentiment.

Additionally, with further study opportunities, the model input must be scrutinized for another emerging issue: artificial news websites. A substantial amount of website content is currently generated by machine learning algorithms utilizing natural language processing techniques. A portion of those websites are established as news platforms. At a certain juncture, the model may face the issue of machine learning from another machine.

One potential advancement is the ability to compute the DNN with a quantum computer and quantum algorithms. Companies such as D-Wave Quantum provide commercially available quantum computers. This might elevate the model's potential to new heights.

Finally, institutional country risk assessment providers and their models have the advantage of using proprietary data within a much more established framework. This applies to both quantitative and qualitative models, as institutional country risk providers protect not only their quantitative datasets but also the experts who contribute qualitative assessments. The institutions mentioned in Section 4.2 have long-established data collection methodologies, as evidenced by their extensive history of published assessments.

However, this thesis elevates the collection of OSINT data into a databank capable of performing country risk assessments without the need for institutional support. Furthermore, the proposed model enables the data to be assessed in multiple ways, while the use of a neural network remains a promising approach for overcoming the linearity limitations inherent in purely quantitative data.

5. CONCLUSION, RECOMMENDATIONS, POLICY IMPLICATION, AND LIMITATION

5.1 Conclusion and Recommendations

The results show that daily data input into a neural network for assessing country risk can provide a predicted trend analysis for country risk assessment. Multinational corporations (MNCs) seeking a more individualized approach to country risk assessment are provided with a foundation on which the model developed in this thesis can be further extended. By applying the one-day-ahead prediction model in combination with a sufficiently robust database, MNCs could assess risks related to their business operations for each country for which data are collected. However, the model competes with long-established institutional providers. MNCs with sufficient financial resources that can afford the services of providers such as Coface, Fitch Solutions, and other established institutions require a longer period of real-world application before adopting the thesis model.

Contemporary developments, however, increase the likelihood that MNCs will once again internalize country risk assessment capabilities. Following an already turbulent decade, the second term of Donald Trump as President of the United States has reiterated the relevance of the BANI model, illustrated by developments such as the forced extradition of Venezuela's illegitimate president Maduro, the announcement of incorporating Greenland into the United States as part of U.S. security strategy considerations, and the threat of extraordinary taxation of U.S. allies should they fail to comply with demands or actions by the U.S. administration.

The process of internalizing country risk assessment has occurred previously, notably after the Iranian Revolution, and was later dismantled primarily due to cost considerations and a period of relative geopolitical stability for MNCs. The global expansion of MNCs and their international business operations was closely linked to increasing market globalization and the predominance of liberal economic principles. As geopolitical conflicts increasingly reflect traditional hegemonic strategies aimed at securing influence, resources, and national prosperity, MNCs now have renewed incentives to reincorporate country risk assessment models in-house.

For these developments, the model proposed in this thesis provides a strong foundation for further advancement, particularly due to its novel approach to collecting OSINT data within a framework of variables that have proven effective in country risk models over the past century. Multinational corporations (MNCs) have the option to collect OSINT data individually and according to their specific requirements, while still benefiting from the underlying model framework. Furthermore, the use of a deep neural network in this thesis to address the linearity limitations of traditional country risk models aligns closely with another contemporary development.

The rise of large language models and the growing importance for many companies of deploying agents to gain business advantages have led many MNCs to consider internalizing such agents in order to protect customer data. As a result, MNCs are likely to possess greater GPU capacity and computational resources overall. These resources are essential prerequisites for scaling the application of neural networks for country risk assessment within the proposed model, particularly when combined with expanded data collection. Consequently, the recommendations of this thesis must include a call for funding further research in order to gain access to larger datasets. This requirement does not stand in contrast to the proposed OSINT collection approach, as discussed in Chapter 2.8.

From an academic perspective, the field of country risk assessment is likely to experience increased research activity as a result of the developments outlined above. While neural networks have previously been applied in related research, these methods continue to offer substantial potential for further investigation, particularly when models are fine-tuned using individually collected data rather than focusing solely on comparative performance analyses against institutional assessments or rankings. Given the heterogeneous nature of neural network architectures, the scope for developing models specifically tailored to country risk assessment remains broad. For researchers pursuing this direction, a likely next step in the evolution of neural network applications for country risk assessment is the use of world models. Such models would not only analyze data and improve performance through training but could also learn underlying „rules of the world." In the context of country risk assessment, this capability could enable models to evaluate outcomes that are currently monitored by political experts, potentially reducing the need for such expert intervention.

With respect to the role of OSINT data in country risk assessment, the field also presents significant opportunities for further research, particularly in the large-scale application of OSINT data collection. This thesis seeks to contribute novelty to this aspect of country risk assessment. The volume and value of OSINT data, as discussed in Chapter 2.8, indicate its importance for MNCs not only in supporting traditional business operations but also in protecting those operations through informed country risk assessment. Scaling the thesis model, or any comparable model that seeks to aggregate country risk data using OSINT sources, would likely require collaboration with a corporate research partner, as data refinement at larger scales becomes increasingly complex to manage.

5.2 Policy Implication

The results should inform the company about the risks associated with the environment in which it operates, enabling management to evaluate the potential effects on business operations. The company's environment includes not only the host countries of the multinational corporation and its home country but also third-party countries, as risks in those regions can impact the MNC, as illustrated by Bouchet et al. (2003). A comprehensive country risk model should encompass a global environmental assessment, placing greater emphasis on factors that significantly expose business operations to the global environment. The results are organized by variable, necessitating the synthesis of each individual result to create a complete picture for the MNCs. This assessment should empower management to decide whether to proceed with an investment or to halt it, as well as to determine strategies for protecting business operations.

After conducting a country risk assessment, management must decide whether to take mediation actions or to cease investments and business operations. While this research primarily focuses on assessing country risk, it is essential to briefly explore who is responsible for risk mitigation. This exploration can offer explanations for the outcomes of the country risk assessment and any potential delays in reporting information. Mediation actions may involve engaging stakeholders through corporate diplomacy initiatives or reducing operations in host countries.

5.3 Limitation

Recognizing the constraints and therefore the limitation of the model is essential. While the deep neural network can reveal hidden relationships within the input sentiment, it does not possess the insight of a political strategist. For instance, if negative sentiment arises from current political developments—a situation a political strategist might interpret as a temporary trend—the deep neural network requires additional time to adjust the weight of that input. This limitation highlights the necessity for expert input to provide context for some of the results. Since political experts already provide a portion of the model's input data through published reports and news updates, the country risk assessment ecosystem should include expert commentary on the model's results.

To address computing constraints, one can enhance the infrastructure capabilities. Upgrading the MySQL database server from a limited private virtual server to a cloud server would offer virtually limitless scalability. Considering that the model will receive data inputs from thousands of websites daily, the MySQL storage must be sufficient. A notable limitation of this research has been funding; external financial support would enable the expansion of data input and enhance data quality. This was most directly observed in the evaluation of the weekly and monthly country risk assessments, which did not perform to their full potential, most likely due to missing data points. An increase in the availability of financial data could enhance data input across all variables in the model for each country uniformly. Future research into open-source intelligence data gathering for country risk assessments should take this funding issue into consideration.

Although change detection is open source and can also be deployed on a cloud server, a custom-programmed web scraper may provide more precise and efficient data collection. Change detection can monitor an unlimited number of websites, but the selection of the CSS data scraped relies on the integrated Playwright application. Playwright's visual filter isolates CSS elements on the websites, improving the accuracy of the scraping process. Nevertheless, a tailored solution could further refine this process, thereby enhancing the quality of the input data for the deep neural network. Since the quality and volume of input data are defining factors in the training of a neural network, a tailored data collection solution could directly improve the performance of the country risk assessment model.

6. NEW AND NOVEL SCIENTIFIC FINDINGS

The thesis explored the potential of open-source intelligence data gathering, the application of neural networks, and the feasibility of creating a universally applicable country risk model for multinational corporations. The findings are novel, given that the collected data, the timeframe for collection, and the countries examined are unique. Additionally, the results indicate promising avenues for further research in the realm of open-source intelligence analysis and the future utilization of artificial intelligence. Expanding the databases developed for this research, especially with additional funding, could enable a more significant data collection effort.

1. This research demonstrates that average manual efforts cannot achieve the automated collection of open-source data to the same extent. The use of website monitoring software, such as Changedetection, in conjunction with external servers equipped with MySQL databases, allows for the collection of data from hundreds to thousands of websites daily, aided by the Python script developed for this research. The database established in the thesis contains over 44,000 data entries for just five countries. Through API calls, non-English data was sent to OpenAI for translation, and the translated data was subsequently uploaded automatically via API to the MySQL database. Establishing a truly universal open-source intelligence process serves as a foundation for future data collection in country research.
2. Moreover, given the extensive prior research in the field of country risk, this study demonstrated that by augmenting variables and consolidating them into seven comprehensive categories, the future of country risk analysis and artificial intelligence can shift from seeking perfect correlations and regressions between variables to focusing on the most effective analysis of the data derived from these variables.
3. Neural networks can evaluate OSINT data in relation to country risk. By employing sentiment analysis based on tokenization through the TensorFlow library, the neural network can predict positive or negative trends for the country risk data. The neural network has the capability to analyze either the entire country or specific variables pertinent to that country. The predictions generated by the neural network are statistically significant.

7. SUMMARY

This research aimed to develop a new country risk model utilizing open-source intelligence data and advanced machine learning methods, providing multinational corporations with a practical tool for country risk prediction. The hypothesis for this study was predicated on the assumption that the model would yield statistically significant results. The model successfully integrated this type of data, enabling near real-time updates to the underlying database. Although the trend predictions demonstrated significant outcomes, the data collection and wrangling processes faced certain limitations.

Overall, this work made contributions both theoretically, by suggesting future directions for this research field, and methodologically, by demonstrating how new country risk data can be gathered for country risk analysis. A primary limitation of this study relates to the funding of data collection, as not all open-source intelligence data is freely accessible. Additionally, the volume of data scraped for analysis exceeded the scope of this research, preventing the thorough cleaning of every piece of collected intelligence. A more organized and cleaner database could enhance the model's results. MNCs could implement the proposed model and refine it with additional research and resources.

In summary, this research represents a new era of data analysis in country risk assessment through machine learning and artificial intelligence. The abundance of available data necessitates the careful selection of data wrangling techniques and processing methods for country risk models, particularly if scholars and practitioners seek to move beyond preprocessed institutional data inputs. While this research underscores the importance of real-time data processing in country risk analysis and assessment, future studies are likely to advance the field further through innovative computational methods. The global landscape for MNCs will undoubtedly provide ample opportunities for ongoing research in country risk assessment.

8. APPENDICES

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8.2 API-Code

```
#!/usr/bin/env python3
import mysql.connector
import logging
import sys
import time
import requests
import os
import json
from mysql.connector import Error
from flask import Flask, jsonify, request
from langdetect import detect
import openai # openai Version 0.28

app = Flask(__name__)
logging.basicConfig(level=logging.ERROR)
script_dir = os.path.dirname(os.path.abspath(__file__))
config_path = os.path.join(script_dir, "GoldListener2_config.json")
with open(config_path, "r") as config_file:
     config = json.load(config_file)
open_ai_key=config['open_ai_key']
db_host=config['db_host']
db_port=config['db_port']
db_user=config['db_user']
db_passwort=config['db_passwort']
db_database=config['db_database']
db_table=config['db_table']
openai.api_key = open_ai_key
print("Import Config done", file=sys.stderr)

def connect_to_database(host, port, user, password, database, query, data):
    print("Start Connect DB", file=sys.stderr)
    try:
        connection = mysql.connector.connect(
            host=host,
            port=port,
            user=user,
            password=password,
            database=database
        )
```

```
        if connection.is_connected():
            print("Connection to the database established.", file=sys.stderr)

            cursor = connection.cursor()
            cursor.execute(query, data)
            results = cursor.fetchall()
            for row in results:
                print(row, file=sys.stderr)
            connection.commit()
            cursor.close()
            connection.close()

            print("Connection to the database closed.", file=sys.stderr)

    except Error as e:
        print(f"Error connecting to the database: {e}", file=sys.stderr)

@app.route("/api", methods=['GET', 'POST'])
def get_answer():
    print(request , file=sys.stderr)
    data = request.get_json()
    print(data , file=sys.stderr)

    j_insert_time = time.strftime("%Y-%m-%d %H:%M:%S")
    j_webpage = data["WEBPAGE"]
    j_old_data = data["OLD_DATA"]
    j_new_data = data["NEW_DATA"][0:4999]
    j_watch_tag = data["WATCH_TAG"]

    print(j_insert_time , file=sys.stderr)
    print(j_webpage , file=sys.stderr)
    print(j_old_data, file=sys.stderr)
    print(j_new_data , file=sys.stderr)
    print(j_watch_tag , file=sys.stderr)

    host=db_host
    port = db_port
    user = db_user
    password = db_passwort
    database = db_database
    table = db_table

    query = (f"INSERT INTO `{database}`.`{table}` (`INSERT_TIME`, `WEBPAGE`, `OLD_DATA`, `NEW_DATA`,
`COUNTRY`, `VARIABLE`, `LANGUAGE`, `NEW_DATA_TRANSLATED` ) VALUES (%s, %s, %s, %s, %s, %s, %s, %s );" )
    print('starte query', file=sys.stderr)
    print(query, file=sys.stderr)
```

```
    j_country =''
    j_variable =''
    if j_watch_tag.count('_')>=1:
        watch_tag_Arr = j_watch_tag.split('_')
        j_country =watch_tag_Arr[0]
        j_variable =watch_tag_Arr[1]
    print('detect language', file=sys.stderr)
    languageVar = detect(j_new_data)

    new_data_translated= ''
    if languageVar != 'en':
        print('language: en', file=sys.stderr)
        new_data_translated = translate_text(j_new_data, 'english')

    data = (j_insert_time, j_webpage, j_old_data, j_new_data, j_country, j_variable,languageVar,
new_data_translated)
    connect_to_database(host, port, user, password, database, query, data)

    #Wait for connection
    print('start wait', file=sys.stderr)
    time.sleep(10)
    print('wait end', file=sys.stderr)

    return j_webpage


def translate_text(text_to_translate, target_language):
     print("Start translate", file=sys.stderr)
     translated_text=''
     try:
       response = openai.ChatCompletion.create(
            model="gpt-3.5-turbo",
            messages=[
                {"role": "system", "content": f"You are a translator. Translate this text into
{target_language}."},
                {"role": "user", "content": text_to_translate}
            ]
        )
       translated_text = response['choices'][0]['message']['content']
       translated_text = " ".join(translated_text.split())
       print(f"Translated text:{translated_text}", file=sys.stderr)
     except Exception as e:
         print(f"Error at openai while translating:{e}", file=sys.stderr)
     return translated_text

if __name__ == '__main__':
    app.run(debug=True, host='0.0.0.0', port=9000)
```

Appendix 8.2. *listener* Code *Source*: Author

8.3 Deep Neural Network - R code

```
library(tidyverse)
library(tidytext)
library(plotly)
library(htmlwidgets)
library(keras)
library(dplyr)
library(iml)




# Load and Configure SentiWordNet
sentiwordnet_path <- "C:/Users/user/Desktop/SentiWordNet_3.0.0.txt"

sentiwordnet <- read_delim(
  sentiwordnet_path,
  delim = "\t",
  comment = "#",
  col_names = c("POS", "ID", "PosScore", "NegScore", "SynsetTerms", "Gloss"),
  col_types = cols_only(
    POS = col_character(),
    PosScore = col_double(),
    NegScore = col_double(),
    SynsetTerms = col_character()
  )
)

# Split SynsetTerms into single words
sentiwordnet_tokens <- sentiwordnet %>%
  separate_rows(SynsetTerms, sep = " ") %>%
  mutate(
    word = str_remove(SynsetTerms, "#[0-9]+"),
    positive = PosScore,
    negative = NegScore,
    objective = 1 - (PosScore + NegScore)
  ) %>%
  select(word, positive, negative, objective)
```

```
# Tokenize words
tokens <- workstation %>%
  mutate(newCol = coalesce(NEW_DATA_TRANSLATED,NEW_DATA)) %>%
  filter(!is.na(VARIABLE)) %>%
  #filter(!is.na(NEW_DATA_TRANSLATED)) %>%
  filter(VARIABLE == 'ene') %>%
  filter(COUNTRY == 'MEX') %>%
  #filter(INSERT_TIME < '2025-03-17') %>%
  #filter(LANGUAGE == 'es') %>%
  #filter(VARIABLE %in% c('env')) %>%
  #filter(!VARIABLE %in% c('gov')) %>%  ## -> not in (x y z)
  #mutate(text = coalesce(NEW_DATA,NEW_DATA_TRANSLATED) %>%
  select(ID, VARIABLE, text = newCol) %>%
  #mutate(text = ifelse(is.na(NEW_DATA), NEW_DATA_TRANSLATED, NEW_DATA))
  #select(ID, VARIABLE, text = coalesce(!!!select(., any_of(c("NEW_DATA", "NEW_DATA_TRANSLATED"))))) %>%
  #select(ID, VARIABLE, text = ifelse(is.na(NEW_DATA), NEW_DATA_TRANSLATED, NEW_DATA)) %>%

  unnest_tokens(word, text)


# Link with SentiWordNet
tokens_with_sentiment <- tokens %>%
  inner_join(sentiwordnet_tokens, by = "word")

# Calculate Sentiment-Scores
text_sentiments <- tokens_with_sentiment %>%
  group_by(ID, VARIABLE) %>%
  summarise(
    positive = sum(positive, na.rm = TRUE),
    negative = sum(negative, na.rm = TRUE),
    objective = sum(objective, na.rm = TRUE),
    net_sentiment = sum(positive - negative, na.rm = TRUE)
  ) %>%
  ungroup()
```

```r
# K-means Clustering per variable
clustered_results <- list()

for (var in unique(text_sentiments$VARIABLE)) {
  data <- text_sentiments %>% filter(VARIABLE == var)
  num_points <- nrow(data)

  if (num_points >= 2) {
    k <- min(3, num_points)
    set.seed(123)
    kmeans_result <- kmeans(data %>% select(positive, negative), centers = k)

    data <- data %>%
      mutate(cluster = as.factor(kmeans_result$cluster))
  } else {
    warning(paste("Insufficient data", var))
    data <- data %>% mutate(cluster = NA)
  }
  clustered_results[[var]] <- data
}

final_data <- bind_rows(clustered_results)

# Pseudo target variable and neural network
final_data <- final_data %>%
  group_by(VARIABLE) %>%
  arrange(ID) %>%
  mutate(
    trend = case_when(
      lead(net_sentiment, default = first(net_sentiment)) > net_sentiment ~ 1,
      TRUE ~ 0
    )
  ) %>%
  ungroup() %>%
  filter(!is.na(trend))

nn_data <- final_data %>%
  mutate(
    positive = scale(positive),
    negative = scale(negative),
    objective = scale(objective)
  ) %>%
  select(positive, negative, objective, trend)

set.seed(123)
train_indices <- sample(1:nrow(nn_data), size = 0.8 * nrow(nn_data))
train_data <- nn_data[train_indices, ]
test_data <- nn_data[-train_indices, ]

x_train <- as.matrix(train_data %>% select(positive, negative, objective))
y_train <- train_data$trend
x_test <- as.matrix(test_data %>% select(positive, negative, objective))
y_test <- test_data$trend
```

```r
# Deep Neural Network Architecture
nn_model <- keras_model_sequential() %>%
  layer_dense(units = 128, activation = "relu", input_shape = c(3)) %>%
  layer_dropout(rate = 0.3) %>%
  layer_dense(units = 128, activation = "relu") %>%
  layer_dropout(rate = 0.3) %>%
  layer_dense(units = 64, activation = "relu") %>%
  layer_dropout(rate = 0.2) %>%
  layer_dense(units = 32, activation = "relu") %>%
  layer_dropout(rate = 0.2) %>%
  layer_dense(units = 1, activation = "sigmoid")

nn_model %>% compile(
  optimizer = optimizer_adam(learning_rate = 0.001),
  loss = "binary_crossentropy",
  metrics = c("accuracy")
)

summary(nn_model)

history <- nn_model %>% fit(
  x = x_train,
  y = y_train,
  epochs = 100,
  batch_size = 16,
  validation_split = 0.2,
  callbacks = list(
    callback_early_stopping(monitor = "val_loss", patience = 10, restore_best_weights = TRUE)
  )
)

evaluation <- nn_model %>% evaluate(x_test, y_test)
cat("Test Loss:", evaluation[1], "Test Accuracy:", evaluation[2], "\n")

final_data <- final_data %>%
  mutate(
    predicted_trend = nn_model %>% predict(as.matrix(select(final_data, positive, negative, objective)))
%>% as.vector()
  )
```

```r
# 3D-Scatterplot with timeline
timespan <- Sys.Date() - as.Date("2024-12-08")
text_sentiments <- text_sentiments %>%
  mutate(time = as.POSIXct("2024-12-08") + runif(nrow(text_sentiments), 0, 86400 * timespan))

text_sentiments <- text_sentiments %>% arrange(time)

plot_with_nn <- plot_ly(
  final_data,
  x = ~positive,
  y = ~negative,
  z = ~objective,
  color = ~predicted_trend,
  symbol = ~VARIABLE,
  text = ~paste("ID:", ID,
                "<br>Net Sentiment:", net_sentiment,
                "<br>Variable:", VARIABLE,
                "<br>Predicted Trend:", round(predicted_trend, 2)),
  type = "scatter3d",
  mode = "markers",
  marker = list(size = 5)
) %>%
  layout(
    title = "3D Sentiment Scatterplot",
    scene = list(
      xaxis = list(title = "Positive Score"),
      yaxis = list(title = "Negative Score"),
      zaxis = list(title = "Objective Score")
    )
  )

timeline <- plot_ly(
  text_sentiments,
  x = ~time,
  y = ~net_sentiment,
  type = "scatter",
  mode = "lines+markers",
  line = list(color = "black"),
  marker = list(color = "red", size = 5)
) %>%
  layout(
    title = "Zeitstrahl der Sentiments",
    xaxis = list(title = "Time"),
    yaxis = list(title = "Net Sentiment")
  )

combined_plot <- subplot(plot_with_nn, timeline, nrows = 2, heights = c(0.7, 0.3))
output_nn_file <- "3d_sentiment_nn_trends.html"
saveWidget(combined_plot, file = output_nn_file)
browseURL(output_nn_file)
```

```r
# 3D-Scatterplot for clustering
plot_with_clusters <- plot_ly(
  final_data,
  x = ~positive,
  y = ~negative,
  z = ~objective,
  color = ~cluster,
  symbol = ~VARIABLE,
  text = ~paste("ID:", ID,
                "<br>Net Sentiment:", net_sentiment,
                "<br>Variable:", VARIABLE,
                "<br>Cluster:", cluster),
  type = "scatter3d",
  mode = "markers",
  marker = list(size = 5)
) %>%
  layout(
    title = "3D Sentiment Scatterplot (Clustering Results)",
    scene = list(
      xaxis = list(title = "Positive Score"),
      yaxis = list(title = "Negative Score"),
      zaxis = list(title = "Objective Score")
    )
  )

output_cluster_file <- "3d_sentiment_clusters.html"
saveWidget(plot_with_clusters, file = output_cluster_file)
browseURL(output_cluster_file)

# Extract weights and biases from the trained model
weights_and_biases <- nn_model$get_weights()

# Function to display weights and biases layer by layer
for (i in seq(1, length(weights_and_biases), by = 2)) {
  layer_number <- (i + 1) / 2

  cat("\n====================================\n")
  cat("Layer", layer_number, "Details\n")
  cat("====================================\n")

  # Extract weights and biases
  weights <- weights_and_biases[[i]]
  biases <- weights_and_biases[[i + 1]]

  # Print weight matrix dimensions
  cat("Weight Matrix Dimensions: ", dim(weights), "\n")

  # Print first few weights
  cat("First 5 Weights:\n")
  print(weights[1:min(5, length(weights))])
```

```r
  # Print biases
  cat("\nBiases:\n")
  print(biases)

  cat("\n-------------------------------------\n")
}

# Saves the trained Model
# save_model_hdf5(nn_model, "sentiment_nn_model.h5")

# Loading the saved Model
# loaded_model <- load_model_hdf5("sentiment_nn_model.h5")

# Prediction with loaded Model
# predicted_trend <- loaded_model %>% predict(new_data)

# SHAP (Shapley Additive Explanations)
# Convert test data to a data frame
x_test_df <- as.data.frame(x_test)
colnames(x_test_df) <- c("positive", "negative", "objective")

# Wrap trained model for SHAP analysis
predictor <- Predictor$new(
  model = nn_model,
  data = x_test_df,
  y = y_test
)

# Compute SHAP values for the first test instance
shapley_values <- Shapley$new(predictor, x_test_df[1, , drop = FALSE])

# Plot SHAP values
plot(shapley_values)

# LIME for Keras Neural Network
# Load the lime package
library(lime)

# Prepare training data as data frame
train_df <- as.data.frame(x_train)
colnames(train_df) <- c("positive", "negative", "objective")

# Prepare a test instance to explain
instance_to_explain <- as.data.frame(x_test[1, , drop = FALSE])
colnames(instance_to_explain) <- c("positive", "negative", "objective")

# Wrap the Keras model into a custom class
keras_wrapper <- list(model = nn_model)
class(keras_wrapper) <- "keras_wrapper"
```

```
  # Print biases
  cat("\nBiases:\n")
  print(biases)

  cat("\n------------------------------------\n")
}

# Saves the trained Model
# save_model_hdf5(nn_model, "sentiment_nn_model.h5")

# Loading the saved Model
# loaded_model <- load_model_hdf5("sentiment_nn_model.h5")

# Prediction with loaded Model
# predicted_trend <- loaded_model %>% predict(new_data)

# SHAP (Shapley Additive Explanations)
# Convert test data to a data frame
x_test_df <- as.data.frame(x_test)
colnames(x_test_df) <- c("positive", "negative", "objective")

# Wrap trained model for SHAP analysis
predictor <- Predictor$new(
  model = nn_model,
  data = x_test_df,
  y = y_test
)

# Compute SHAP values for the first test instance
shapley_values <- Shapley$new(predictor, x_test_df[1, , drop = FALSE])

# Plot SHAP values
plot(shapley_values)

# LIME for Keras Neural Network
# Load the lime package
library(lime)

# Prepare training data as data frame
train_df <- as.data.frame(x_train)
colnames(train_df) <- c("positive", "negative", "objective")

# Prepare a test instance to explain
instance_to_explain <- as.data.frame(x_test[1, , drop = FALSE])
colnames(instance_to_explain) <- c("positive", "negative", "objective")

# Wrap the Keras model into a custom class
keras_wrapper <- list(model = nn_model)
class(keras_wrapper) <- "keras_wrapper"
```

```r
# Define model_type method for lime
model_type.keras_wrapper <- function(x, ...) {
  return("classification")
}

# Define predict_model method for lime
predict_model.keras_wrapper <- function(x, newdata, type = "raw", ...) {
  preds <- predict(x$model, as.matrix(newdata))
  return(data.frame(`1` = preds))
}

# Create lime explainer object
explainer <- lime(
  x = train_df,
  model = keras_wrapper,
  bin_continuous = TRUE
)

# Run explanation for one instance
lime_explanation <- explain(
  instance_to_explain,
  explainer,
  n_features = 3,
  labels = 1
)

# Output results
print(lime_explanation)

# Plot LIME feature contributions
plot_features(lime_explanation)
```

Appendix 8.3. Deep Neural Network Code *Source*: Author

8.4 K-Fold Code

```
library(keras)
library(tensorflow)
library(dplyr)
library(tibble)
library(purrr)
library(yardstick)
library(ggplot2)


nn_data <- nn_data %>%
  mutate(across(c(positive, negative, objective), scale)) %>%
  select(positive, negative, objective, trend)

k <- 5
set.seed(123)
folds <- cut(seq(1, nrow(nn_data)), breaks = k, labels = FALSE)

cv_results <- map_df(1:k, function(i) {
  cat("\nFold", i, "\n--------------------\n")

  test_indices <- which(folds == i)
  test_fold <- nn_data[test_indices, ]
  train_fold <- nn_data[-test_indices, ]

  x_train_cv <- as.matrix(train_fold %>% select(positive, negative, objective))
  y_train_cv <- train_fold$trend
  x_test_cv <- as.matrix(test_fold %>% select(positive, negative, objective))
  y_test_cv <- test_fold$trend

  model_cv <- keras_model_sequential() %>%
    layer_dense(units = 128, activation = "relu", input_shape = c(3)) %>%
    layer_dropout(rate = 0.3) %>%
    layer_dense(units = 128, activation = "relu") %>%
    layer_dropout(rate = 0.3) %>%
    layer_dense(units = 64, activation = "relu") %>%
    layer_dropout(rate = 0.2) %>%
    layer_dense(units = 32, activation = "relu") %>%
    layer_dropout(rate = 0.2) %>%
    layer_dense(units = 1, activation = "sigmoid")

  model_cv %>% compile(
    optimizer = optimizer_adam(learning_rate = 0.001),
    loss = "binary_crossentropy",
    metrics = "accuracy"
  )
```

```r
  model_cv %>% fit(
    x_train_cv, y_train_cv,
    epochs = 100,
    batch_size = 16,
    validation_split = 0.2,
    verbose = 0,
    callbacks = list(
      callback_early_stopping(monitor = "val_loss", patience = 10, restore_best_weights = TRUE)
    )
  )

  preds_prob <- model_cv %>% predict(x_test_cv) %>% as.vector()
  preds_label <- ifelse(preds_prob >= 0.5, 1, 0)

  results <- tibble(
    truth = factor(y_test_cv, levels = c(0, 1)),
    prediction = factor(preds_label, levels = c(0, 1)),
    prob = preds_prob
  )

  acc <- accuracy(results, truth = truth, estimate = prediction)$.estimate
  prec <- precision(results, truth = truth, estimate = prediction)$.estimate
  rec <- recall(results, truth = truth, estimate = prediction)$.estimate
  f1 <- f_meas(results, truth = truth, estimate = prediction)$.estimate
  auc <- roc_auc_vec(truth = results$truth, estimate = results$prob, event_level = "second")

  tibble(
    fold = i,
    accuracy = acc,
    precision = prec,
    recall = rec,
    f1_score = f1,
    auc = auc
  )
})

print(cv_results)
```

```
cv_summary <- cv_results %>%
  summarise(across(where(is.numeric), mean, .names = "mean_{.col}"))

print(cv_summary)

cv_results_long <- cv_results %>%
  pivot_longer(cols = -fold, names_to = "metric", values_to = "value")

ggplot(cv_results_long, aes(x = factor(fold), y = value, fill = metric)) +
  geom_col(position = "dodge") +
  labs(
    title = "K-Fold Cross-Validation Metric",
    x = "Fold",
    y = "Value",
    fill = "Metric"
  ) +
  theme_minimal() +
  scale_y_continuous(labels = scales::percent_format(accuracy = 1))
o(f, seed, [])
}
```

Appendix 8.4. K-fold analysis code *Source*: Author

8.5 Weekly prediction code

```r
library(tidyverse)
library(tidytext)
library(stringr)
library(lubridate)
library(zoo)
library(keras)
library(dplyr)
library(lime)
library(iml)
library(pROC)

set.seed(123) # used to stabilize noisy data

# Weekly prediction code
sentiwordnet_path <- "C:/Users/user/Desktop/SentiWordNet_3.0.0.txt"
target_variable   <- "gov"
target_country    <- "MEX"
stop_date         <- as.Date("2025-12-01")
expl_h            <- 1
k_folds           <- 5
epochs_main       <- 100
epochs_cv         <- 60
batch_size        <- 16
patience_es       <- 10
learning_rate     <- 0.001


# "positive vs non-positive"
cls_threshold_y    <- 0     # y_true_bin = 1 if y > 0 else 0
cls_threshold_pred <- 0     # y_pred_bin = 1 if pred > 0 else 0

# a/b division
safe_div <- function(a, b) ifelse(b == 0, NA_real_, a / b)

# helper for K-fold analysis
calc_cls_metrics <- function(y_true_cont, y_score_cont,
                             thr_y = cls_threshold_y, thr_pred = cls_threshold_pred) {
  ok <- is.finite(y_true_cont) & is.finite(y_score_cont)
  y_true_cont  <- y_true_cont[ok]
  y_score_cont <- y_score_cont[ok]

  if (length(y_true_cont) < 2) {
    return(tibble(
      accuracy = NA_real_, precision = NA_real_, recall = NA_real_, f1 = NA_real_, auc = NA_real_,
      support = length(y_true_cont),
      pos_rate = ifelse(length(y_true_cont) == 0, NA_real_, mean(y_true_cont > thr_y))
    ))
  }

  y_true <- ifelse(y_true_cont > thr_y, 1L, 0L)
  y_pred <- ifelse(y_score_cont > thr_pred, 1L, 0L)
```

```r
  TP <- sum(y_true == 1L & y_pred == 1L)
  TN <- sum(y_true == 0L & y_pred == 0L)
  FP <- sum(y_true == 0L & y_pred == 1L)
  FN <- sum(y_true == 1L & y_pred == 0L)

  acc  <- safe_div(TP + TN, TP + TN + FP + FN)
  prec <- safe_div(TP, TP + FP)
  rec  <- safe_div(TP, TP + FN)
  f1   <- ifelse(is.na(prec) | is.na(rec) | (prec + rec) == 0, NA_real_, 2 * prec * rec / (prec + rec))

  auc_val <- NA_real_
  if (length(unique(y_true)) == 2) {
    r <- suppressWarnings(pROC::roc(response = y_true, predictor = y_score_cont, quiet = TRUE))
    auc_val <- as.numeric(pROC::auc(r))
  }

  tibble(
    accuracy = acc,
    precision = prec,
    recall = rec,
    f1 = f1,
    auc = auc_val,
    support = length(y_true),
    pos_rate = mean(y_true == 1L)
  )
}

if (!inherits(workstation$INSERT_TIME, "POSIXt") && !inherits(workstation$INSERT_TIME, "Date")) {
  workstation <- workstation %>%
    mutate(INSERT_TIME = ymd_hms(INSERT_TIME, quiet = TRUE))
}

# Load & Configure SentiWordNet
sentiwordnet <- read_delim(
  sentiwordnet_path,
  delim = "\t",
  comment = "#",
  col_names = c("POS", "ID", "PosScore", "NegScore", "SynsetTerms", "Gloss"),
  col_types = cols_only(
    POS = col_character(),
    PosScore = col_double(),
    NegScore = col_double(),
    SynsetTerms = col_character()
  )
)

sentiwordnet_tokens <- sentiwordnet %>%
  separate_rows(SynsetTerms, sep = " ") %>%
  mutate(
    word      = str_remove(SynsetTerms, "#[0-9]+"),
    positive  = PosScore,
    negative  = NegScore,
    objective = 1 - (PosScore + NegScore)
  ) %>%
  select(word, positive, negative, objective)
```

```r
# Tokenize, join sentiments
tokens <- workstation %>%
  mutate(newCol = coalesce(NEW_DATA_TRANSLATED, NEW_DATA)) %>%
  filter(!is.na(newCol)) %>%
  filter(VARIABLE == target_variable, COUNTRY == target_country) %>%
  select(ID, VARIABLE, COUNTRY, INSERT_TIME, text = newCol) %>%
  unnest_tokens(word, text)

tokens_with_sentiment <- tokens %>%
  inner_join(sentiwordnet_tokens, by = "word")

# Daily aggregation
daily <- tokens_with_sentiment %>%
  mutate(date = as.Date(INSERT_TIME)) %>%
  group_by(VARIABLE, date) %>%
  summarise(
    positive      = sum(positive, na.rm = TRUE),
    negative      = sum(negative, na.rm = TRUE),
    objective     = sum(objective, na.rm = TRUE),
    net_sentiment = sum(positive - negative, na.rm = TRUE),
    .groups = "drop"
  ) %>%
  arrange(VARIABLE, date) %>%
  filter(VARIABLE == target_variable)

# Lag features + rolling stats
lag_k     <- 7
feat_cols <- c("net_sentiment", "positive", "negative", "objective")

mk_lags <- function(df, cols, L) {
  for (c in cols) {
    for (h in 1:L) {
      df[[paste0(c, "_lag", h)]] <- dplyr::lag(df[[c]], h)
    }
  }
  df
}

daily_feat <- daily %>%
  arrange(date) %>%
  mutate(
    net_ma3 = zoo::rollmean(net_sentiment, 3, fill = NA, align = "right"),
    net_ma7 = zoo::rollmean(net_sentiment, 7, fill = NA, align = "right"),
    net_sd7 = zoo::rollapply(net_sentiment, 7, sd, fill = NA, align = "right")
  ) %>%
  mk_lags(c(feat_cols, "net_ma3", "net_ma7", "net_sd7"), lag_k)

# week ahead targets
for (h in 1:7) {
  daily_feat[[paste0("y_h", h)]] <- dplyr::lead(daily_feat$net_sentiment, h)
}
target_cols <- paste0("y_h", 1:7)
```

```r
# Train/Test by time stop
pred_dates <- seq(from = stop_date + 1, by = "day", length.out = 7)

train_df <- daily_feat %>%
  filter(date <= stop_date) %>%
  filter(!if_any(all_of(target_cols), is.na))

pred_row <- daily_feat %>%
  filter(date == stop_date)

print(train_df)

if (nrow(train_df) < 50) warning("Very few training rows; model quality may suffer.")
if (nrow(pred_row) != 1) stop("No unique row for stop_date found.")

# Feature selection
lag_cols <- names(daily_feat) %>%
  (\(nms) nms[grepl("(_lag[1-7]$)|(net_ma[37]_lag[1-7]$)|(net_sd7_lag[1-7]$)", nms)])()

base_lags <- grep("^(net_sentiment|positive|negative|objective)_lag[1-7]$", names(daily_feat), value =
TRUE)
if (length(lag_cols) == 0 && length(base_lags) > 0) lag_cols <- base_lags
if (length(lag_cols) == 0) stop("No lag features found. Check lag creation.")

train_df <- train_df %>% filter(!if_any(all_of(lag_cols), is.na))

# Scaling parameters from training only
mu  <- sapply(train_df[lag_cols], mean, na.rm = TRUE)
sdv <- sapply(train_df[lag_cols], sd,   na.rm = TRUE)
sdv[sdv == 0 | is.na(sdv)] <- 1

scaleX <- function(df) {
  X <- as.data.frame(df[lag_cols])
  for (j in seq_along(lag_cols)) {
    X[[j]] <- (X[[j]] - mu[j]) / sdv[j]
  }
  as.matrix(X)
}

x_train <- scaleX(train_df)
y_train <- as.matrix(train_df[target_cols])

if (any(is.na(pred_row[lag_cols]))) stop("Prediction row has missing lag features.")
x_pred <- scaleX(pred_row)
```

```r
# Model builders
build_model <- function(input_dim, lr = learning_rate) {
  keras_model_sequential() %>%
    layer_dense(units = 128, activation = "relu", input_shape = input_dim) %>%
    layer_dropout(rate = 0.3) %>%
    layer_dense(units = 64, activation = "relu") %>%
    layer_dropout(rate = 0.2) %>%
    layer_dense(units = 7, activation = "linear") %>%
    compile(
      optimizer = optimizer_adam(learning_rate = lr),
      loss = "mse",
      metrics = list("mae")
    )
}

fit_model <- function(model, x, y, epochs, val_split = 0.2, shuffle = FALSE, batch_size_arg =
batch_size) {
  model %>% fit(
    x = x, y = y,
    epochs = epochs,
    batch_size = batch_size,
    validation_split = val_split,
    shuffle = shuffle,
    callbacks = list(
      callback_early_stopping(monitor = "val_loss", patience = patience_es, restore_best_weights =
TRUE),
      callback_reduce_lr_on_plateau(
        monitor = "val_loss",
        factor = 0.5,
        patience = 5,
        min_lr = 1e-5,
        verbose = 1
      )
    )

  )
}

# Rolling K-fold on training era

train_dates <- sort(unique(train_df$date))
if (length(train_dates) < (k_folds + 14)) {
  warning("Few unique train dates for the requested k_folds; reduce k_folds if needed.")
}
```

```r
make_rolling_splits <- function(dates, k) {
  n <- length(dates)
  cuts <- floor(seq(from = floor(n*0.5), to = n-1, length.out = k+1))  # start CV in the second half
  splits <- list()
  for (i in 1:k) {
    train_end <- dates[cuts[i]]
    val_end   <- dates[cuts[i+1]]
    val_start <- dates[cuts[i] + 1]
    splits[[i]] <- list(train_end = train_end, val_start = val_start, val_end = val_end)
  }
  splits
}

roll_splits <- make_rolling_splits(train_dates, k_folds)

# CV metrics
cv_metrics <- tibble(
  fold = integer(), horizon = integer(),
  accuracy = double(), precision = double(), recall = double(), f1 = double(), auc = double(),
  support = integer(),
  train_end = as.Date(character()), val_start = as.Date(character()), val_end = as.Date(character())
)

for (i in seq_along(roll_splits)) {
  sp <- roll_splits[[i]]
  tr <- train_df %>% filter(date <= sp$train_end)
  vl <- train_df %>% filter(date >= sp$val_start, date <= sp$val_end)

  if (nrow(tr) < 1 || nrow(vl) < 1) next

# Recompute scaling per fold (train-only)
  mu_cv  <- sapply(tr[lag_cols], mean, na.rm = TRUE)
  sdv_cv <- sapply(tr[lag_cols], sd,   na.rm = TRUE); sdv_cv[sdv_cv == 0 | is.na(sdv_cv)] <- 1
  scaleX_cv <- function(df) {
    X <- as.data.frame(df[lag_cols])
    for (j in seq_along(lag_cols)) X[[j]] <- (X[[j]] - mu_cv[j]) / sdv_cv[j]
    as.matrix(X)
  }

  x_tr <- scaleX_cv(tr); y_tr <- as.matrix(tr[target_cols])
  x_vl <- scaleX_cv(vl); y_vl <- as.matrix(vl[target_cols])

  mdl <- build_model(ncol(x_tr))
  hist <- fit_model(mdl, x_tr, y_tr, epochs = epochs_cv, val_split = 0.0, shuffle = FALSE,
batch_size_arg = batch_size)
  preds <- mdl %>% predict(x_vl)  # [n_val x 7]
```

```r
# classification metrics
  for (h in 1:7) {
    m <- calc_cls_metrics(
      y_true_cont  = y_vl[, h],
      y_score_cont = preds[, h],
      thr_y = cls_threshold_y,
      thr_pred = cls_threshold_pred
    )

    cv_metrics <- add_row(cv_metrics,
                          fold = i, horizon = h,
                          accuracy = m$accuracy,
                          precision = m$precision,
                          recall = m$recall,
                          f1 = m$f1,
                          auc = m$auc,
                          support = as.integer(m$support),
                          train_end = sp$train_end,
                          val_start = sp$val_start, val_end = sp$val_end
    )
  }
}

# mean calculation
cat("\n==== Rolling K-fold CV summary (MEAN classification metrics across folds + horizons) ====\n")
mean_metrics <- cv_metrics %>%
  summarise(
    mean_accuracy  = mean(accuracy, na.rm = TRUE),
    mean_precision = mean(precision, na.rm = TRUE),
    mean_recall    = mean(recall, na.rm = TRUE),
    mean_f1        = mean(f1, na.rm = TRUE),
    mean_auc       = mean(auc, na.rm = TRUE)
  )
print(mean_metrics)

# Train final model on full training era
input_dim <- ncol(x_train)
nn_model  <- build_model(input_dim)
history   <- fit_model(nn_model, x_train, y_train, epochs = epochs_main, val_split = 0.2, shuffle =
FALSE)

# 7-day forecast
pred_7  <- as.numeric(nn_model %>% predict(x_pred))
forecast <- tibble(
  date = seq(from = stop_date + 1, by = "day", length.out = 7),
  net_sentiment_pred = pred_7
)
cat("\n==== 7-day forecast ====\n")
print(forecast)
write_csv(forecast, "forecast_7day_net_sentiment.csv")
```

```r
# LIME
keras_multiout_wrapper <- list(model = nn_model,
                               lag_cols = lag_cols,
                               mu = mu,
                               sdv = sdv,
                               horizon = expl_h)
class(keras_multiout_wrapper) <- "keras_multiout_wrapper"

model_type.keras_multiout_wrapper <- function(x, ...) "regression"

predict_model.keras_multiout_wrapper <- function(x, newdata, type = "raw", ...) {

  X <- as.data.frame(newdata[, x$lag_cols, drop = FALSE])
  for (j in seq_along(x$lag_cols)) {
    X[[j]] <- (X[[j]] - x$mu[j]) / x$sdv[j]
  }
  preds <- predict(x$model, as.matrix(X))

  data.frame(Response = as.numeric(preds[, x$horizon]))
}

train_feats_unscaled <- train_df[, lag_cols, drop = FALSE]
explainer <- lime(
  x = train_feats_unscaled,
  model = keras_multiout_wrapper,
  bin_continuous = TRUE
)

instance_to_explain <- pred_row[, lag_cols, drop = FALSE]
lime_explanation <- explain(
  instance_to_explain,
  explainer,
  n_features = min(8, length(lag_cols)),
  n_labels = 1
)

cat("\n==== LIME explanation (horizon ", expl_h, ") ====\n", sep = "")
print(lime_explanation)

plot_features(lime_explanation)

# SHAP
predict_fun_iml <- function(newdata) {
  X <- as.data.frame(newdata[, lag_cols, drop = FALSE])
  for (j in seq_along(lag_cols)) X[[j]] <- (X[[j]] - mu[j]) / sdv[j]
  preds <- predict(nn_model, as.matrix(X))
  as.numeric(preds[, expl_h])
}

x_iml <- train_df[, lag_cols, drop = FALSE]
```

```
predictor_iml <- Predictor$new(
  model = NULL,
  data  = x_iml,
  y     = train_df[[target_cols[expl_h]]],
  predict.function = predict_fun_iml
)

x_shap <- pred_row[, lag_cols, drop = FALSE]
shapley_values <- Shapley$new(predictor_iml, x.interest = x_shap)

cat("\n==== SHAP (iml) results for one instance, horizon ", expl_h, " ====\n", sep = "")
print(shapley_values$results)

# plot(shapley_values)
```

Appendix 8.5. Weekly prediction code *Source*: Author

8.6 Monthly prediction code

```
library(tidyverse)
library(tidytext)
library(stringr)
library(lubridate)
library(zoo)
library(keras)
library(dplyr)
library(lime)
library(iml)
library(pROC)

set.seed(123)
tensorflow::set_random_seed(123) # again used to stabilize noisy data

sentiwordnet_path <- "C:/Users/user/Desktop/SentiWordNet_3.0.0.txt"
target_variable   <- "gov"
target_country    <- "MEX"
stop_date         <- as.Date("2025-12-01")
expl_h            <- 1
k_folds           <- 5
epochs_main       <- 100
epochs_cv         <- 60
batch_size        <- 16
patience_es       <- 10
learning_rate     <- 0.001

# Classification thresholds
cls_threshold_y    <- 0     # y_true_bin = 1 if y > 0 else 0
cls_threshold_pred <- 0     # y_pred_bin = 1 if pred > 0 else 0

# helper for K-fold analysis
safe_div <- function(a, b) ifelse(b == 0, NA_real_, a / b)

calc_cls_metrics <- function(y_true_cont, y_score_cont,
                             thr_y = cls_threshold_y, thr_pred = cls_threshold_pred) {
  ok <- is.finite(y_true_cont) & is.finite(y_score_cont)
  y_true_cont  <- y_true_cont[ok]
  y_score_cont <- y_score_cont[ok]

  if (length(y_true_cont) < 2) {
    return(tibble(
      accuracy = NA_real_, precision = NA_real_, recall = NA_real_, f1 = NA_real_, auc = NA_real_,
      support = length(y_true_cont),
      pos_rate = ifelse(length(y_true_cont) == 0, NA_real_, mean(y_true_cont > thr_y))
    ))
  }

  y_true <- ifelse(y_true_cont > thr_y, 1L, 0L)
  y_pred <- ifelse(y_score_cont > thr_pred, 1L, 0L)
```

```
  TP <- sum(y_true == 1L & y_pred == 1L)
  TN <- sum(y_true == 0L & y_pred == 0L)
  FP <- sum(y_true == 0L & y_pred == 1L)
  FN <- sum(y_true == 1L & y_pred == 0L)

  acc  <- safe_div(TP + TN, TP + TN + FP + FN)
  prec <- safe_div(TP, TP + FP)
  rec  <- safe_div(TP, TP + FN)
  f1   <- ifelse(is.na(prec) | is.na(rec) | (prec + rec) == 0, NA_real_, 2 * prec * rec / (prec + rec))

  auc_val <- NA_real_
  if (length(unique(y_true)) == 2) {
    r <- suppressWarnings(pROC::roc(response = y_true, predictor = y_score_cont, quiet = TRUE))
    auc_val <- as.numeric(pROC::auc(r))
  }

  tibble(
    accuracy = acc,
    precision = prec,
    recall = rec,
    f1 = f1,
    auc = auc_val,
    support = length(y_true),
    pos_rate = mean(y_true == 1L)
  )
}

# time format
if (!inherits(workstation$INSERT_TIME, "POSIXt") && !inherits(workstation$INSERT_TIME, "Date")) {
  workstation <- workstation %>%
    mutate(INSERT_TIME = ymd_hms(INSERT_TIME, quiet = TRUE))
}

# Load & Configure SentiWordNet
sentiwordnet <- read_delim(
  sentiwordnet_path,
  delim = "\t",
  comment = "#",
  col_names = c("POS", "ID", "PosScore", "NegScore", "SynsetTerms", "Gloss"),
  col_types = cols_only(
    POS = col_character(),
    PosScore = col_double(),
    NegScore = col_double(),
    SynsetTerms = col_character()
  )
)

sentiwordnet_tokens <- sentiwordnet %>%
  separate_rows(SynsetTerms, sep = " ") %>%
  mutate(
    word      = str_remove(SynsetTerms, "#[0-9]+"),
    positive  = PosScore,
    negative  = NegScore,
    objective = 1 - (PosScore + NegScore)
  ) %>%
  select(word, positive, negative, objective)
```

```r
# Tokenize, join sentiments
tokens <- workstation %>%
  mutate(newCol = coalesce(NEW_DATA_TRANSLATED, NEW_DATA)) %>%
  filter(!is.na(newCol)) %>%
  filter(VARIABLE == target_variable, COUNTRY == target_country) %>%
  select(ID, VARIABLE, COUNTRY, INSERT_TIME, text = newCol) %>%
  unnest_tokens(word, text)

tokens_with_sentiment <- tokens %>%
  inner_join(sentiwordnet_tokens, by = "word")

# Daily aggregation
daily <- tokens_with_sentiment %>%
  mutate(date = as.Date(INSERT_TIME)) %>%
  group_by(VARIABLE, date) %>%
  summarise(
    positive      = sum(positive, na.rm = TRUE),
    negative      = sum(negative, na.rm = TRUE),
    objective     = sum(objective, na.rm = TRUE),
    net_sentiment = sum(positive - negative, na.rm = TRUE),
    .groups = "drop"
  ) %>%
  arrange(VARIABLE, date) %>%
  filter(VARIABLE == target_variable)

# Lag features + rolling stats
lag_k     <- 30
feat_cols <- c("net_sentiment", "positive", "negative", "objective")

mk_lags <- function(df, cols, L) {
  for (c in cols) {
    for (h in 1:L) {
      df[[paste0(c, "_lag", h)]] <- dplyr::lag(df[[c]], h)
    }
  }
  df
}

daily_feat <- daily %>%
  arrange(date) %>%
  mutate(
    net_ma15 = zoo::rollmean(net_sentiment, 15, fill = NA, align = "right"),
    net_ma30 = zoo::rollmean(net_sentiment, 30, fill = NA, align = "right"),
    net_sd30 = zoo::rollapply(net_sentiment, 30, sd, fill = NA, align = "right")
  ) %>%
  mk_lags(c(feat_cols, "net_ma15", "net_ma30", "net_sd30"), lag_k)

#  month-ahead prediction targets
for (h in 1:30) {
  daily_feat[[paste0("y_h", h)]] <- dplyr::lead(daily_feat$net_sentiment, h)
}
target_cols <- paste0("y_h", 1:30)
```

```r
# Train/Test by time stop
pred_dates <- seq(from = stop_date + 1, by = "day", length.out = 30)

train_df <- daily_feat %>%
  filter(date <= stop_date) %>%
  filter(!if_any(all_of(target_cols), is.na))

pred_row <- daily_feat %>%
  filter(date == stop_date)

if (nrow(train_df) < 50) warning("Very few training rows; model quality may suffer.")
if (nrow(pred_row) != 1) stop("No unique row for stop_date found.")

# Feature selection
lag_cols <- names(daily_feat) %>%
  (\(nms) nms[grepl("(_lag[1-30]$)|(net_ma(15|30)_lag[1-30]$)|(net_sd30_lag[1-30]$)", nms)])()

# fallback
base_lags <- grep("^(net_sentiment|positive|negative|objective)_lag[1-30]$", names(daily_feat), value =
TRUE)
if (length(lag_cols) == 0 && length(base_lags) > 0) lag_cols <- base_lags
if (length(lag_cols) == 0) stop("No lag features found. Check lag creation.")

train_df <- train_df %>% filter(!if_any(all_of(lag_cols), is.na))
if (any(is.na(pred_row[lag_cols]))) stop("Prediction row has missing lag features.")

# training only (final model + explainability)
mu  <- sapply(train_df[lag_cols], mean, na.rm = TRUE)
sdv <- sapply(train_df[lag_cols], sd,   na.rm = TRUE)
sdv[sdv == 0 | is.na(sdv)] <- 1

scaleX <- function(df, mu_vec, sd_vec, cols) {
  X <- as.data.frame(df[cols])
  for (j in seq_along(cols)) X[[j]] <- (X[[j]] - mu_vec[j]) / sd_vec[j]
  as.matrix(X)
}

x_train <- scaleX(train_df, mu, sdv, lag_cols)
y_train <- as.matrix(train_df[target_cols])
x_pred  <- scaleX(pred_row,  mu, sdv, lag_cols)

# Model builders
build_model <- function(input_dim, lr = learning_rate) {
  keras_model_sequential() %>%
    layer_dense(units = 128, activation = "relu", input_shape = input_dim) %>%
    layer_dropout(rate = 0.3) %>%
    layer_dense(units = 64, activation = "relu") %>%
    layer_dropout(rate = 0.2) %>%
    layer_dense(units = 30, activation = "linear") %>%
    compile(
      optimizer = optimizer_adam(learning_rate = lr),
      loss = "mse",
      metrics = list("mae")
    )
}
```

```
fit_model <- function(model, x, y, epochs, val_split = 0.2, shuffle = FALSE, batch_size_arg =
batch_size) {
  model %>% fit(
    x = x, y = y,
    epochs = epochs,
    batch_size = batch_size_arg,
    validation_split = val_split,
    shuffle = shuffle,
    callbacks = list(
      callback_early_stopping(monitor = "val_loss", patience = patience_es, restore_best_weights =
TRUE),
      callback_reduce_lr_on_plateau(
        monitor = "val_loss",
        factor = 0.5,
        patience = 5,
        min_lr = 1e-5,
        verbose = 1
      )
    )
  )
}

#  Rolling K-fold
train_dates <- sort(unique(train_df$date))
if (length(train_dates) < (k_folds + 14)) {
  warning("Few unique train dates for the requested k_folds; reduce k_folds if needed.")
}

make_rolling_splits <- function(dates, k) {
  n <- length(dates)
  cuts <- floor(seq(from = floor(n * 0.5), to = n - 1, length.out = k + 1))
  splits <- list()
  for (i in 1:k) {
    train_end <- dates[cuts[i]]
    val_end   <- dates[cuts[i + 1]]
    val_start <- dates[cuts[i] + 1]
    splits[[i]] <- list(train_end = train_end, val_start = val_start, val_end = val_end)
  }
  splits
}

roll_splits <- make_rolling_splits(train_dates, k_folds)

cv_metrics <- tibble(
  fold = integer(), horizon = integer(),
  accuracy = double(), precision = double(), recall = double(), f1 = double(), auc = double(),
  support = integer(), pos_rate = double(),
  n_pos = integer(), n_neg = integer(),
  train_end = as.Date(character()), val_start = as.Date(character()), val_end = as.Date(character())
)
```

```r
for (i in seq_along(roll_splits)) {
  sp <- roll_splits[[i]]
  tr <- train_df %>% filter(date <= sp$train_end)
  vl <- train_df %>% filter(date >= sp$val_start, date <= sp$val_end)

  if (nrow(tr) < 10 || nrow(vl) < 2) next

# fold scaling (train-only)
  mu_cv  <- sapply(tr[lag_cols], mean, na.rm = TRUE)
  sdv_cv <- sapply(tr[lag_cols], sd,   na.rm = TRUE)
  sdv_cv[sdv_cv == 0 | is.na(sdv_cv)] <- 1

  scaleX_cv <- function(df) scaleX(df, mu_cv, sdv_cv, lag_cols)

  x_tr <- scaleX_cv(tr); y_tr <- as.matrix(tr[target_cols])
  x_vl <- scaleX_cv(vl); y_vl <- as.matrix(vl[target_cols])

  mdl  <- build_model(ncol(x_tr))
  hist <- fit_model(mdl, x_tr, y_tr, epochs = epochs_cv, val_split = 0.0, shuffle = FALSE,
batch_size_arg = batch_size)
  preds <- mdl %>% predict(x_vl)  # [n_val x 30]

  for (h in 1:30) {
    m <- calc_cls_metrics(
      y_true_cont  = y_vl[, h],
      y_score_cont = preds[, h],
      thr_y = cls_threshold_y,
      thr_pred = cls_threshold_pred
    )

    y_true_bin <- ifelse(y_vl[, h] > cls_threshold_y, 1L, 0L)
    n_pos <- sum(y_true_bin == 1L, na.rm = TRUE)
    n_neg <- sum(y_true_bin == 0L, na.rm = TRUE)

    cv_metrics <- add_row(
      cv_metrics,
      fold = i, horizon = h,
      accuracy = m$accuracy, precision = m$precision, recall = m$recall, f1 = m$f1, auc = m$auc,
      support = as.integer(m$support), pos_rate = m$pos_rate,
      n_pos = as.integer(n_pos), n_neg = as.integer(n_neg),
      train_end = sp$train_end, val_start = sp$val_start, val_end = sp$val_end
    )
  }
}
```

```r
cat("\n==== Rolling K-fold CV summary (per horizon) ====\n")
print(
  cv_metrics %>%
    group_by(horizon) %>%
    summarise(
      accuracy = mean(accuracy, na.rm = TRUE),
      precision = mean(precision, na.rm = TRUE),
      recall = mean(recall, na.rm = TRUE),
      f1 = mean(f1, na.rm = TRUE),
      auc = mean(auc, na.rm = TRUE),
      avg_support = mean(support, na.rm = TRUE),
      avg_pos_rate = mean(pos_rate, na.rm = TRUE),
      frac_single_class = mean(n_pos == 0 | n_neg == 0, na.rm = TRUE),
      .groups = "drop"
    )
)

cat("\n==== Rolling K-fold CV summary (MEAN classification metrics across folds + horizons) ====\n")
mean_metrics <- cv_metrics %>%
  summarise(
    mean_accuracy  = mean(accuracy, na.rm = TRUE),
    mean_precision = mean(precision, na.rm = TRUE),
    mean_recall    = mean(recall, na.rm = TRUE),
    mean_f1        = mean(f1, na.rm = TRUE),
    mean_auc       = mean(auc, na.rm = TRUE)
  )
print(mean_metrics)

cat("\n==== Diagnostic: how often validation windows are single-class ====\n")
print(
  cv_metrics %>%
    summarise(
      frac_single_class = mean(n_pos == 0 | n_neg == 0, na.rm = TRUE),
      mean_pos_rate = mean(pos_rate, na.rm = TRUE),
      mean_support = mean(support, na.rm = TRUE)
    )
)

# Train final model on full training era
input_dim <- ncol(x_train)
nn_model  <- build_model(input_dim)
history   <- fit_model(nn_model, x_train, y_train, epochs = epochs_main, val_split = 0.2, shuffle =
FALSE)

# monthly forecast
pred_30 <- as.numeric(nn_model %>% predict(x_pred))

forecast <- tibble(
  date = seq(from = stop_date + 1, by = "day", length.out = 30),
  net_sentiment_pred = pred_30
)
```

```r
cat("\n==== 30-day forecast ====\n")
print(forecast, n = 30)
write_csv(forecast, "forecast_30day_net_sentiment.csv")

# LIME
keras_multiout_wrapper <- list(
  model   = nn_model,
  lag_cols = lag_cols,
  mu      = mu,
  sdv     = sdv,
  horizon = expl_h
)
class(keras_multiout_wrapper) <- "keras_multiout_wrapper"

model_type.keras_multiout_wrapper <- function(x, ...) "regression"

predict_model.keras_multiout_wrapper <- function(x, newdata, type = "raw", ...) {
  X <- as.data.frame(newdata[, x$lag_cols, drop = FALSE])
  for (j in seq_along(x$lag_cols)) X[[j]] <- (X[[j]] - x$mu[j]) / x$sdv[j]
  preds <- predict(x$model, as.matrix(X))
  data.frame(Response = as.numeric(preds[, x$horizon]))
}

train_feats_unscaled <- train_df[, lag_cols, drop = FALSE]

explainer <- lime(
  x = train_feats_unscaled,
  model = keras_multiout_wrapper,
  bin_continuous = TRUE
)

instance_to_explain <- pred_row[, lag_cols, drop = FALSE]

lime_explanation <- explain(
  instance_to_explain,
  explainer,
  n_features = min(8, length(lag_cols)),
  n_labels = 1
)

cat("\n==== LIME explanation (horizon ", expl_h, ") ====\n", sep = "")
print(lime_explanation)
#plot_features(lime_explanation)

# SHAP
predict_fun_iml <- function(newdata) {
  X <- as.data.frame(newdata[, lag_cols, drop = FALSE])
  for (j in seq_along(lag_cols)) X[[j]] <- (X[[j]] - mu[j]) / sdv[j]
  preds <- predict(nn_model, as.matrix(X))
  as.numeric(preds[, expl_h])
}

x_iml <- train_df[, lag_cols, drop = FALSE]
```

```r
predictor_iml <- Predictor$new(
  model = NULL,
  data  = x_iml,
  y     = train_df[[target_cols[expl_h]]],
  predict.function = predict_fun_iml
)

x_shap <- pred_row[, lag_cols, drop = FALSE]
shapley_values <- Shapley$new(predictor_iml, x.interest = x_shap)

cat("\n==== SHAP (iml) results for one instance, horizon ", expl_h, " ====\n", sep = "")
print(shapley_values$results)

 plot(shapley_values)
```

Appendix 8.6. Monthly prediction code *Source*: Author

8.7 R connect code

```r
library(RMySQL)

connObj <- dbConnect(MySQL(), user='***', password='***', dbname='***', host='***.***.***.***')

workstation <- dbReadTable(connObj, '***')

data.frame(workstation)

dbDisconnect(connObj)
```

Appendix 8.7. R connect code *Source*: Author

8.8 OSINT Link Collection

COUNTRY	VARIABLE	WEBPAGE
GER	eco	https://www.br.de/nachrichten/wirtschaft,QXAPwyN
GER	eco	https://www.Coface.com/news-economy-and-insights/business-risk-dashboard/country-risk-files/germany
GER	eco	https://www.deutschland.de/en/germany-economy
GER	eco	https://www.deutschlandfunk.de/wirtschaft-106.html
GER	eco	https://www.dw.com/en/german-economy/t-19112011
GER	eco	https://www.euronews.com/tag/german-economy
GER	eco	https://www.faz.net/aktuell/finanzen/thema/ezb
GER	eco	https://www.faz.net/aktuell/rhein-main/wirtschaft/
GER	eco	https://www.faz.net/aktuell/wirtschaft/
GER	eco	https://www.faz.net/aktuell/wirtschaft/thema/deutsche-bundesbank
GER	eco	https://www.focus.de/finanzen/news/
GER	eco	https://www.ft.com/german-economy
GER	eco	https://www.handelsblatt.com/politik/konjunktur/
GER	eco	https://www.ifw-kiel.de/topics/economic-outlook/
GER	eco	https://www.mdr.de/nachrichten/deutschland/wirtschaft/index.html
GER	eco	https://www.ndr.de/nachrichten/info/Banken,banken181.html
GER	eco	https://www.ndr.de/nachrichten/info/Konjunktur,konjunktur177.html
GER	eco	https://www.sueddeutsche.de/thema/Banken_und_Finanzindustrie
GER	eco	https://www.sueddeutsche.de/thema/Bundesbank
GER	eco	https://www.sueddeutsche.de/thema/Unternehmen
GER	eco	https://www.sueddeutsche.de/thema/Wirtschaftspolitik
GER	eco	https://www.tagesschau.de/wirtschaft
GER	eco	https://www.tagesschau.de/wirtschaft/finanzen
GER	eco	https://www.vdi-nachrichten.com/wirtschaft/konjunktur/
GER	eco	https://www.vdi-nachrichten.com/wirtschaft/unternehmen/
GER	eco	https://www.zdf.de/nachrichten/wirtschaft
GER	eco	https://www.zeit.de/thema/inflation
GER	eco	https://www.zeit.de/thema/konjunktur
GER	ene	https://energy.einnews.com/country/germany
GER	ene	https://www.br.de/nachrichten/themen/energie,UIbgFQD

GER	ene	https://www.faz.net/aktuell/wirtschaft/thema/energiekrise
GER	ene	https://www.faz.net/aktuell/wirtschaft/thema/energieversorgung
GER	ene	https://www.faz.net/aktuell/wirtschaft/thema/energiewende
GER	ene	https://www.faz.net/aktuell/wirtschaft/thema/erneuerbare-energien
GER	ene	https://www.handelsblatt.com/unternehmen/energie/
GER	ene	https://www.ndr.de/nachrichten/info/Energie,energie281.html
GER	ene	https://www.ndr.de/nachrichten/info/energiekrise122_page-1.html
GER	ene	https://www.ndr.de/nachrichten/info/Energiewende,energiewende433.html
GER	ene	https://www.rechargenews.com/tag/germany
GER	ene	https://www.spiegel.de/thema/energiewende/
GER	ene	https://www.sueddeutsche.de/thema/Energie
GER	ene	https://www.swr.de/swraktuell/swraktuell-suche-100.html?swx_keyword=Energieandswx_restriction=%2Fswraktuellandswx_sort=date
GER	ene	https://www.tagesschau.de/wirtschaft/energie
GER	ene	https://www.vdi-nachrichten.com/technik/energie/
GER	ene	https://www.zdf.de/nachrichten/thema/energiesparen-100.html
GER	ene	https://www.zdf.de/nachrichten/thema/energiewende-erneuerbare-energien-100.html
GER	ene	https://www.zeit.de/thema/energiewende
GER	env	https://presseportal.greenpeace.de/
GER	env	https://www.bmwk.de/SiteGlobals/BMWI/Forms/Listen/Medienraum/Medienraum_Formular.html?documentType_=PressRelease
GER	env	https://www.duh.de/presse/pressemitteilungen/
GER	env	https://www.germanwatch.org/de
GER	env	https://www.germanwatch.org/de/presse
GER	env	https://www.klima-allianz.de/presse/pressespiegel
GER	env	https://www.tagesschau.de/thema/klimawandel
GER	env	https://www.welt.de/wissenschaft/umwelt/
GER	env	https://www.zeit.de/thema/umweltschutz
GER	env	https://presseportal.greenpeace.de/
GER	env	https://www.bmwk.de/SiteGlobals/BMWI/Forms/Listen/Medienraum/Medienraum_Formular.html?documentType_=PressRelease
GER	env	https://www.br.de/nachrichten/suche/?param=Klimaschutz
GER	env	https://www.deutschland.de/en/topic/environment
GER	env	https://www.duh.de/presse/pressemitteilungen/

GER	env	https://www.germanwatch.org/de
GER	env	https://www.germanwatch.org/de/presse
GER	env	https://www.handelsblatt.com/themen/umweltschutz
GER	env	https://www.klima-allianz.de/presse/pressespiegel
GER	env	https://www.mdr.de/wissen/klima/index.html
GER	env	https://www.n-tv.de/thema/umweltbundesamt
GER	env	https://www.ndr.de/home/Der-Klimawandel-im-Norden-Folgen-Ideen-und-Perspektiven,klimawandelnorden100.html
GER	env	https://www.ndr.de/nachrichten/info/Klimaschutz,klimaschutz358.html
GER	env	https://www.ndr.de/nachrichten/info/Umweltpolitik,umweltpolitik103.html
GER	env	https://www.sueddeutsche.de/thema/Klimapolitik
GER	env	https://www.tagesschau.de/thema/klimawandel
GER	env	https://www.tagesschau.de/wissen/klima
GER	env	https://www.vdi-nachrichten.com/technik/umwelt/
GER	env	https://www.welt.de/wissenschaft/umwelt/
GER	env	https://www.zdf.de/nachrichten/thema/klimawandel-186.html
GER	env	https://www.zeit.de/thema/umweltschutz
GER	gov	https://www.br.de/nachrichten/alles-zur-bundestagswahl,S8YieJ6
GER	gov	https://www.br.de/nachrichten/suche/?param=Bundestag
GER	gov	https://www.deutschland.de/en/topic/politics
GER	gov	https://www.deutschlandfunk.de/politikportal-100.html
GER	gov	https://www.faz.net/aktuell/politik/inland/
GER	gov	https://www.focus.de/politik/deutschland/
GER	gov	https://www.handelsblatt.com/politik/deutschland/
GER	gov	https://www.kas.de/de/web/die-politische-meinung/blog
GER	gov	https://www.morgenpost.de/politik/afd/
GER	gov	https://www.morgenpost.de/politik/cdu/
GER	gov	https://www.morgenpost.de/politik/spd/
GER	gov	https://www.n-tv.de/thema/die-linke
GER	gov	https://www.rbb24.de/politik/
GER	gov	https://www.spiegel.de/politik/deutschland/
GER	gov	https://www.spiegel.de/thema/alternative_fuer_deutschland/
GER	gov	https://www.spiegel.de/thema/bundesregierung/
GER	gov	https://www.spiegel.de/thema/bundestagswahl-2025/
GER	gov	https://www.spiegel.de/thema/cdu/
GER	gov	https://www.spiegel.de/thema/csu/

GER	gov	https://www.sueddeutsche.de/thema/Bundesregierung
GER	gov	https://www.sueddeutsche.de/thema/Bundestag
GER	gov	https://www.tagesschau.de/inland/bundestagswahl
GER	gov	https://www.tagesschau.de/inland/innenpolitik
GER	gov	https://www.tagesspiegel.de/politik/
GER	gov	https://www.vdi-nachrichten.com/wirtschaft/politik/
GER	gov	https://www.zdf.de/nachrichten/politik/deutschland
GER	gov	https://www.zeit.de/thema/bundesregierung
GER	gov	https://www.zeit.de/thema/fdp
GER	gov	https://www.zeit.de/thema/spd
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GER	leg	https://www.tagesschau.de/thema/bundesverfassungsgericht
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GER	leg	https://www.zdf.de/nachrichten/thema/bundesgerichtshof-bgh-100.html
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GER	leg	https://www.zeit.de/thema/bundestag
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GER	sec	https://www.br.de/nachrichten/suche/?param=Polizei
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GER	sec	https://www.morgenpost.de/berlin/polizei-berlin/
GER	sec	https://www.n-tv.de/thema/attentate
GER	sec	https://www.n-tv.de/thema/bundeswehr
GER	sec	https://www.n-tv.de/thema/kriminalitaet
GER	sec	https://www.n-tv.de/thema/polizei
GER	sec	https://www.ndr.de/nachrichten/info/Terrorismus,terrorismus111.html
GER	sec	https://www.sueddeutsche.de/thema/Innere_Sicherheit
GER	sec	https://www.sueddeutsche.de/thema/Polizei
GER	sec	https://www.swr.de/swraktuell/swraktuell-suche-100.html?swx_keyword=Polizei+und+Rettungskr%C3%A4fteandswx_restriction=%2Fswraktuellandswx_sort=date
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GER	sec	https://www.zdf.de/nachrichten/panorama/kriminalitaet
GER	sec	https://www.zeit.de/thema/bundeswehr
GER	sec	https://www.zeit.de/thema/kriminalitaet
GER	sec	https://www.zeit.de/thema/polizei
GER	sec	https://www.zeit.de/thema/sicherheitspolitik
GER	sec	https://www.zeit.de/thema/toetungsdelikt
GER	soc	https://corporate.dw.com/en/press-release-archive/s-68340094
GER	soc	https://www.br.de/nachrichten/suche/?param=Demonstration
GER	soc	https://www.br.de/nachrichten/suche/?param=Warnstreiks
GER	soc	https://www.deutschland.de/en/news
GER	soc	https://www.deutschland.de/en/topic/culture
GER	soc	https://www.dw.com/en/top-stories/s-9097
GER	soc	https://www.faz.net/aktuell/wirtschaft/thema/streik
GER	soc	https://www.n-tv.de/thema/demonstrationen
GER	soc	https://www.n-tv.de/thema/streiks

GER	soc	https://www.ndr.de/nachrichten/info/Gewerkschaften,gewerkschaften117.html
GER	soc	https://www.ndr.de/nachrichten/info/Tarifpolitik,tarifpolitik101.html
GER	soc	https://www.spiegel.de/wirtschaft/soziales/
GER	soc	https://www.sueddeutsche.de/thema/Proteste
GER	soc	https://www.sueddeutsche.de/thema/Soziales
GER	soc	https://www.swr.de/swraktuell/swraktuell-suche-100.html?swx_keyword=Protestandswx_restriction=%2Fswraktuellandswx_sort=date
GER	soc	https://www.tagesschau.de/suche#/article/1/?searchText=protest
GER	soc	https://www.thelocal.de/category/living-in-germany
GER	soc	https://www.w3newspapers.com/germany/
GER	soc	https://www.zdf.de/nachrichten/thema/streik-142.html
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GHA	eco	https://citinewsroom.com/category/business/
GHA	eco	https://dailyguidenetwork.com/category/business-news/
GHA	eco	https://ghanaiantimes.com.gh/category/business/
GHA	eco	https://gna.org.gh/business/
GHA	eco	https://gna.org.gh/economic-data/
GHA	eco	https://gna.org.gh/economy/
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GHA	eco	https://starrfm.com.gh/category/business/
GHA	eco	https://thebftonline.com/category/business/
GHA	eco	https://thebftonline.com/category/economy/
GHA	eco	https://tradingeconomics.com/ghana/news
GHA	eco	https://www.businessghana.com/site/news/business
GHA	eco	https://www.Coface.com/news-economy-and-insights/business-risk-dashboard/country-risk-files/ghana
GHA	eco	https://www.ghanabusinessnews.com/category/investment/
GHA	eco	https://www.ghanaweb.com/GhanaHomePage/business/
GHA	eco	https://www.graphic.com.gh/business
GHA	eco	https://www.graphic.com.gh/business/business-news.html
GHA	eco	https://www.graphic.com.gh/business/gb-companies.html?types[0]=1
GHA	eco	https://www.modernghana.com/ghanahome/business/
GHA	eco	https://www.myjoyonline.com/business/economy/
GHA	eco	https://www.pulse.com.gh/business

GHA	eco	https://www.worldbank.org/en/country/ghana
GHA	ene	https://3news.com/business/energy/
GHA	ene	https://citinewsroom.com/tag/oil-and-gas/
GHA	ene	https://dailyguidenetwork.com/?s=energy
GHA	ene	https://energycapitalpower.com/tag/ghana/
GHA	ene	https://energynewsafrica.com/?s=ghana
GHA	ene	https://ghanatoday.gov.gh/category/sector-news/energy/
GHA	ene	https://gna.org.gh/?s=energy
GHA	ene	https://gna.org.gh/?s=petroleum+commission
GHA	ene	https://newsghana.com.gh/?s=energy
GHA	ene	https://starrfm.com.gh/?s=energy
GHA	ene	https://thebftonline.com/category/business/energy/
GHA	ene	https://thebftonline.com/category/commodities/oil-and-gas/
GHA	ene	https://www.ghanaweb.com/GhanaHomePage/NewsArchive/dossier.php?ID=142
GHA	ene	https://www.modernghana.com/section/oilgas
GHA	ene	https://www.myjoyonline.com/tag/gnpc/
GHA	ene	https://www.myjoyonline.com/tag/petroleum-commission/
GHA	ene	https://www.primenewsghana.com/search-ghana-news.html?searchword=energy%20Ghanaandsearchphrase=allandlimit=10
GHA	ene	https://www.todaygh.com/?s=GNPC
GHA	ene	https://www.upstreamonline.com/tag/ghana
GHA	ene	https://yen.com.gh/business-economy/energy/
GHA	env	https://africaclimatereports.org/?s=ghana
GHA	env	https://citinewsroom.com/tag/epa/
GHA	env	https://dailyguidenetwork.com/?s=climate#
GHA	env	https://fcghana.org/category/news-media/
GHA	env	https://gna.org.gh/?s=climate+change+Ghana
GHA	env	https://gna.org.gh/?s=environmental
GHA	env	https://gna.org.gh/?s=pollution+Ghana
GHA	env	https://gna.org.gh/environment/
GHA	env	https://mpecgh.org/news/
GHA	env	https://news.mongabay.com/list/ghana/
GHA	env	https://newsghana.com.gh/science-and-technology-news/environmental-news/
GHA	env	https://starrfm.com.gh/?s=environment

GHA	env	https://thebftonline.com/?s=environment
GHA	env	https://thebftonline.com/?s=pollution
GHA	env	https://thechronicle.com.gh/?s=climate
GHA	env	https://thechronicle.com.gh/?s=pollution
GHA	env	https://www.ghanaenvironment.com/category/ghana-environmental-issues-and-news/
GHA	env	https://www.myjoyonline.com/?s=environment
GHA	env	https://www.myjoyonline.com/?s=pollution+Ghana
GHA	gov	https://3news.com/news/politics/
GHA	gov	https://3news.com/tag/ndc/
GHA	gov	https://3news.com/tag/npp/
GHA	gov	https://citinewsroom.com/politics/
GHA	gov	https://dailyguidenetwork.com/category/political-news/
GHA	gov	https://ghanaiantimes.com.gh/category/politics/
GHA	gov	https://gna.org.gh/politics/
GHA	gov	https://mofep.gov.gh/news
GHA	gov	https://newsghana.com.gh/ghana-news/politics/
GHA	gov	https://starrfm.com.gh/category/politics/
GHA	gov	https://starrfm.com.gh/tag/john-dramani-mahama/
GHA	gov	https://starrfm.com.gh/tag/ndc/
GHA	gov	https://starrfm.com.gh/tag/npp/
GHA	gov	https://www.graphic.com.gh/election2024-updates.html?types[0]=1
GHA	gov	https://www.graphic.com.gh/news/politics.html
GHA	gov	https://www.myjoyonline.com/ghana-election/?election=19
GHA	gov	https://www.myjoyonline.com/news/politics/
GHA	gov	https://www.primenewsghana.com/politics.html
GHA	gov	https://www.pulse.com.gh/news/politics
GHA	gov	https://yen.com.gh/politics/
GHA	gov	https://yen.com.gh/tags/national-democratic-congress-ndc/
GHA	gov	https://yen.com.gh/tags/npp-new-patriotic-party/
GHA	leg	https://3news.com/tag/chief-justice/
GHA	leg	https://citinewsroom.com/?s=parliament
GHA	leg	https://citinewsroom.com/?s=supreme+court
GHA	leg	https://ghanaiantimes.com.gh/?s=parliament
GHA	leg	https://gna.org.gh/?s=supreme+court
GHA	leg	https://starrfm.com.gh/?s=supreme+court

GHA	leg	https://thechronicle.com.gh/?s=supreme+court
GHA	leg	https://www.myjoyonline.com/?s=supreme+court
GHA	leg	https://www.primenewsghana.com/search-ghana-news.html?searchword=parliamentandsearchphrase=allandlimit=10
GHA	leg	https://www.primenewsghana.com/search-ghana-news.html?searchword=supreme%20courtandsearchphrase=all
GHA	leg	https://www.pulse.com.gh/search-results?keywords=supreme%20court
GHA	leg	https://www.todaygh.com/?s=parliament
GHA	leg	https://www.todaygh.com/?s=supreme+court
GHA	leg	https://yen.com.gh/tags/ghana-parliament/
GHA	leg	https://yen.com.gh/tags/supreme-court/
GHA	sec	https://3news.com/news/crime/
GHA	sec	https://3news.com/tag/ghana-police-service/
GHA	sec	https://3news.com/tag/military/
GHA	sec	https://citinewsroom.com/tag/GAF/
GHA	sec	https://citinewsroom.com/tag/military/
GHA	sec	https://citinewsroom.com/tag/police/
GHA	sec	https://dailyguidenetwork.com/tag/police/
GHA	sec	https://ghanaguardian.com/category/crime
GHA	sec	https://ghanaiantimes.com.gh/category/crime/
GHA	sec	https://gna.org.gh/crime/
GHA	sec	https://newsghana.com.gh/ghana-news/crime/
GHA	sec	https://starrfm.com.gh/tag/military/
GHA	sec	https://starrfm.com.gh/tag/police/
GHA	sec	https://starrfm.com.gh/tag/security-agencies/
GHA	sec	https://www.ghanaweb.com/GhanaHomePage/crime/
GHA	sec	https://www.modernghana.com/section/CrimePunishment
GHA	sec	https://www.myjoyonline.com/news/crime/
GHA	sec	https://www.pulse.com.gh/search-results?keywords=arrest
GHA	sec	https://yen.com.gh/tags/ghana-armed-forces/
GHA	sec	https://yen.com.gh/tags/ghana-police-service/
GHA	soc	https://citinewsroom.com/tag/LEAP/
GHA	soc	https://citinewsroom.com/tag/strike/
GHA	soc	https://dailyguidenetwork.com/?s=protest
GHA	soc	https://gna.org.gh/social/
GHA	soc	https://newsghana.com.gh/?s=protest

GHA	soc	https://newswatchgh.com/category/news/social/
GHA	soc	https://starrfm.com.gh/?s=march
GHA	soc	https://starrfm.com.gh/?s=protest
GHA	soc	https://www.gbcghanaonline.com/?s=protest
GHA	soc	https://www.gbcghanaonline.com/?s=strike
GHA	soc	https://www.graphic.com.gh/
GHA	soc	https://www.modernghana.com/section/SocialNews
GHA	soc	https://www.myjoyonline.com/tag/demonstration/
GHA	soc	https://www.myjoyonline.com/tag/social-intervention/
GHA	soc	https://www.myjoyonline.com/tag/strike/
GHA	soc	https://www.pulse.com.gh/search-results?keywords=demonstration
GHA	soc	https://www.pulse.com.gh/search-results?keywords=protest
GHA	soc	https://www.pulse.com.gh/search-results?keywords=protesters
GHA	soc	https://www.todaygh.com/?s=protest
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Appendix 8.5. OSINT Link collection

I would like to express my heartfelt gratitude to my family for their love and unwavering support.

I am also deeply thankful to God for His countless blessings.

I owe special thanks to my cousin, Jens, for his invaluable technical support throughout this endeavor.

Lastly, I would like to extend my sincere appreciation to Dr. Gál, whose patience in taking on this thesis and her insightful advice made these pages possible.