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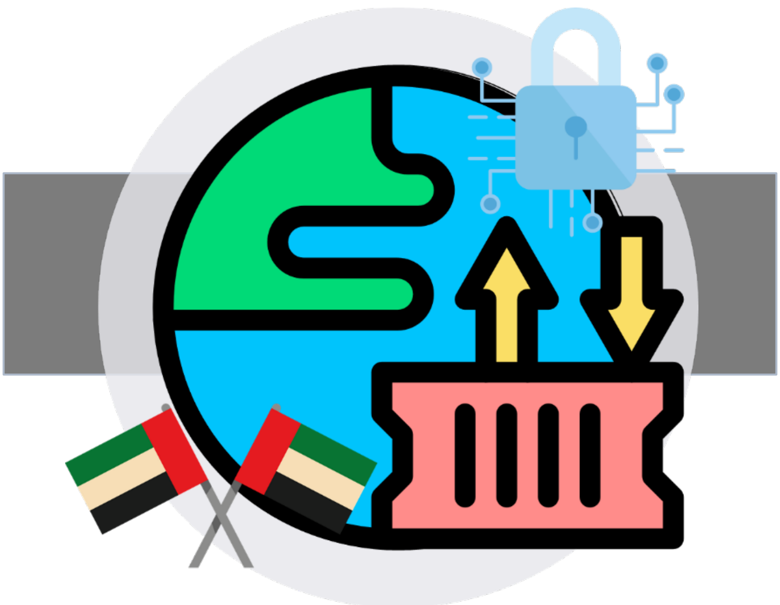
Department of Information Systems and Security

# AN EMPIRICAL STUDY ON THE USE OF SECURE PREDICTIVE ANALYTICS FOR IMPROVING TRADE FORECASTING IN THE UAE

*Asma Salem Alneyadi*



*November 2023*

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Asma Salem Alneyadi

This thesis is submitted in partial fulfilment of the requirements for the degree of Master of Science in Information Security

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Cover: Secure UAE Trade Predictions

(Photo: By Asma Salem Alneyadi)



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## Declaration of Original Work

I, Asma Salem Alneyadi, the undersigned, a graduate student at the United Arab Emirates University (UAEU), and the author of this thesis entitled "*An Empirical Study on the Use of Secure Predictive Analytics for Improving Trade Forecasting in the UAE*", hereby, solemnly declare that this is the original research work done by me under the supervision of Dr. Saed Alrabaee, in the College of Information Technology at UAEU. This work has not previously formed the basis for the award of any academic degree, diploma or a similar title at this or any other university. Any materials borrowed from other sources (whether published or unpublished) and relied upon or included in my thesis have been properly cited and acknowledged in accordance with appropriate academic conventions. I further declare that there is no potential conflict of interest with respect to the research, data collection, authorship, presentation and publication of this thesis.

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Date: 01-11-2023

# Approval of the Master Thesis

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# Abstract

Trade contributes to the United Arab Emirates' economic growth. This thesis focuses on trade dynamics in the UAE using Long Short-Term Memory (LSTM) neural networks. The study focuses on both import and export activities, providing understandings into the complex patterns and impacts of international trade on the UAE's economic growth. The research begins by constructing an LSTM model to forecast the UAE's Gross Domestic Product (GDP) through the utilization of historical trade data. We use time series data for imports and exports as key input features. This innovative approach highlights the relevance of trade statistics as a leading indicator of economic performance.

We utilize the Mean Squared Error (MSE) loss metric and evaluate the correlation matrix, thus ensuring the robustness and precision of our predictions. This evaluation process demonstrates the LSTM model's ability to capture and comprehend the complex interplay of trade patterns and their subsequent impact on the UAE's economic growth.

This study is a significant contribution to the field of economic analysis, as it employs advanced LSTM techniques to discover previously unexplored insights into trade dynamics. By demonstrating the effectiveness of LSTM in forecasting economic variables based on trade data, this research underscores the need for artificial intelligence and machine learning and cryptography to enhance our understanding of the intricate global economic landscape and provide security and confidentiality.

This thesis provides a thorough examination of the UAE's import and export trends, employing LSTM models for GDP prediction, thus fostering a deeper understanding of the nation's economic outlook. The work is not only expanding the horizons of predictive economic analysis but also underscores the potential for intelligent computational techniques to inform and guide policy and decision-making in the context of international trade and economic development. Finally, to ensure the confidentiality, we use homomorphic encryption.

**Keywords:** Trade Analysis, LSTM, predictive analysis, Imports, Exports, RNN, GDP.

# Title and Abstract (in Arabic)

**دراسة تجريبية حول استخدام التحليلات التنبؤية الآمنة لتحسين التنبؤ التجاري في دولة الإمارات العربية المتحدة**


***الملخص***

تساهم التجارة في النمو الاقتصادي لدولة الإمارات العربية المتحدة، تركز هذه الأطروحة على ديناميكيات التجارة في دولة الإمارات العربية المتحدة باستخدام الشبكات العصبية ذات الذاكرة الطويلة قصيرة المدى LSTM ، تركز الدراسة على أنشطة الاستيراد والتصدير، مما يوفر فهمًا للأنماط المعقدة وتأثيرات التجارة الدولية على النمو الاقتصادي في دولة الإمارات العربية المتحدة. يبدأ البحث ببناء نموذج LSTM للتنبؤ بالناتج المحلي الإجمالي لدولة الإمارات العربية المتحدة من خلال استخدام البيانات التجارية التاريخية، نحن نستخدم بيانات السلاسل الزمنية للواردات والصادرات كميزات إدخال رئيسية، ويسلط هذا النهج المبتكر الضوء على أهمية إحصاءات التجارة كمؤشر رئيسي للأداء الاقتصادي.

نحن نستخدم مقياس خسارة متوسط الخطأ التربيعي (MSE) ونقوم بتقييم مصفوفة الارتباط، وبالتالي ضمان قوة ودقة توقعاتنا. توضح عملية التقييم هذه قدرة نموذج LSTM على التقاط وفهم التفاعل المعقد لأنماط التجارة وتأثيرها اللاحق على النمو الاقتصادي في دولة الإمارات العربية المتحدة.

تعد هذه الدراسة مساهمة كبيرة في مجال التحليل الاقتصادي، حيث أنها تستخدم تقنيات LSTM المتقدمة لاكتشاف رؤى غير مستكشفة سابقًا في ديناميكيات التجارة، من خلال إظهار فعالية LSTM في التنبؤ بالمتغيرات الاقتصادية بناءً على البيانات التجارية، يؤكد هذا البحث على الحاجة إلى الذكاء الاصطناعي والتعلم الآلي والتشفير لتعزيز فهمنا للمشهد الاقتصادي العالمي المعقد وتوفير الأمن والسرية.

تقدم هذه الأطروحة دراسة شاملة لاتجاهات الاستيراد والتصدير في دولة الإمارات العربية المتحدة، وذلك باستخدام نماذج LSTM للتنبؤ بالناتج المحلي الإجمالي، وبالتالي تعزيز فهم أعمق للتوقعات الاقتصادية للبلاد، لا يقتصر العمل على توسيع آفاق التحليل الاقتصادي التنبؤي فحسب، بل يؤكد أيضًا على إمكانات التقنيات الحسابية الذكية لإعلام وتوجيه السياسات وصنع القرار في سياق التجارة الدولية والتنمية الاقتصادية، وأخيرًا، لضمان السرية، نستخدم التشفير المتماثل.



**مفاهيم البحث الرئيسية:** تحليل التجارة، LSTM، التحليل التنبؤي، الواردات، الصادرات، RNN، الناتج المحلي الإجمالي.

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I extend my heartfelt gratitude to Dr. Saed Alrabaee, my unwavering mentor and advisor. You are not only an expert in your field but also one of the greatest people I've had the privilege to know. Your endless support, boundless wisdom, and invaluable guidance have illuminated my academic journey. Your belief in my abilities, your patience, and the freedom you've given me to be myself have been transformative. I also thank Dr. Amir and Dr. Omar for their valuable contributions as examiners, enhancing the quality of my thesis and contributing to my success.

To my beloved parents, I owe the deepest debt of gratitude. Your boundless love, unfaltering encouragement, and unwavering belief in me have been the guiding light of my life. Your enduring support has been the wind beneath my wings, propelling me toward my goals. I am truly blessed to have such loving and caring parents, Thank you from the deepest part of my heart, my dearest Mom & Dad. To my cherished friends, your unwavering support and camaraderie during my master's degree journey have warmed my heart. You were not just friends, you were a source of inspiration and motivation. I am grateful for every moment of encouragement, and every uplifting conversation. Special thanks go to Ashikha for being my rock during both the highs and lows.

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# Dedication

*To my beloved parents and family*

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# List of Abbreviations

| | |
|---|---|
| ANN | Artificial Neural Network |
| GDP | Gross Domestic Product |
| LSTM | Long Short-Term Memory |
| MSE | Mean Squared Error |
| NaN | Not-a-Number |
| RNN | Recurrent Neural Network |

# Chapter 1: Introduction

## 1.1 Overview

Global economies are fundamentally very dependent on international trade-in, which is defined as the exchange of goods and services across international boundaries. This allows consumers and countries to access a wide variety of products and services outside of their domestic markets (WTO, 2021). For determining a country's economic situation and potential for growth, it is essential to analyze trade dynamics, including imports, exports, and GDP (WTO, 2021). Understanding the connection between GDP, exports, and imports is extremely necessary for predicting future trends and their effects on economies. Furthermore, international institutions desire the establishment of the World Trade Organization (WTO) to foster and encourage commerce among nations, with varying conditions (WTO, 2021).

The United Arab Emirates' (UAE) imports and exports have evolved significantly over the past decade, reflecting its dynamic economic journey. From its historical significance as a crucial crossroads for ancient trade routes to its modern prominence as a global trade hub, the UAE's trade landscape has witnessed remarkable changes. Early on, its strategic geographical position facilitated a wide range of trade interactions as per Siiner (2016). With the discovery of oil, the UAE's trade dynamics began to undergo a seismic transformation with oil exports propelling its emergence on the global scale (Reynolds & Umekwe 2019).

The historical import and export trends of the Gulf states that maintain commercial relations with the United Arab Emirates (UAE) show a narrative of interconnected economies and shared trade dynamics. Over the past few decades, these trends have reflected not only the economic evolution of each state, but also the symbiotic relationships that bind them within the intricate structure of regional trade.

It becomes evident that the Gulf Cooperation Council (GCC) states, including Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the UAE, have experienced significant trade changes. In the early years, the region's trade primarily centered on traditional commodities and regional exchanges. The Gulf states gradually diversified their trade portfolios, with petroleum and its derivatives becoming the primary source of their exports (Sturm et al., 2008). This shift was particularly pronounced in Saudi Arabia, where oil exports played a significant role in shaping its trade landscape.

In addition, recognizing the major trade affiliates of the UAE further illuminates the intricate network of mutual trade relationships. Although statistical data from sources such as the United Nations Comtrade database and reports by the World Trade Organization provide a quantitative perspective, qualitative analysis highlights the strategic partnerships that have flourished. The UAE's designation as a strategic gateway and trade hub has created strong alliances with trading partners such as China, India, the United States, and other GCC members as stated by Chaziza (2019). These affiliations underscore the multifaceted nature of UAE's trade, spanning various sectors such as energy, technology, and consumer goods.

In the field of trade forecasting, understanding these historical trends and trade affiliations is a compass, guiding predictive models to discern future patterns. By integrating historical data with predictive analytics, the empirical study aims to shed light on the past, but also on the evolving landscape of Gulf states' trade relations and their mutual relations with the UAE. In recent years, a strategic shift towards economic diversification led to a rise in non-oil exports and the development of modern infrastructure (Schwarz, 2008). Today, the UAE's imports and exports encompass a diverse range of industries, highlighting its strategic partnerships and robust economic policies. This evolution provides a foundational basis for our empirical study, where predictive analytics is poised to illuminate the future of UAE's trade forecasting landscape.

To improve trade forecasting globally, predictive analytics has become a useful tool for researchers. The implementation of security measures, in these analytics guarantees the safeguarding of trade information, against access and cyber risks. Researchers have developed predictive models that provide improved accuracy and reliability in predicting future trade patterns and trends using historical trade data and advanced analytical techniques (Zhang et al., 2017). Ensuring the integrity and confidentiality of this data through secure channels enhances the trustworthiness of the predictions. These modern models use statistical techniques and machine learning algorithms (Tang et al., 2022) to find hidden patterns and relationships in trade data, allowing the identification of important variables affecting trade changing aspects. Predictive models have been used in studies to examine, for instance, how trade agreements, geopolitical variables, and macroeconomic indicators affect trade volumes and patterns as stated by Hedström et al. (2020). The security of these predictive analytics systems is crucial, as they handle a plethora of sensitive economic and political data. These models can offer an important understanding of the future course of international trade by including elements like GDP growth rates, exchange rates, and political stability (Joo & Lee, 2021).

The potential of predictive analytics for enhancing trade forecasting has also been recognized by researchers in the United Arab Emirates (UAE). Accurate prediction is essential for the country's economic planning and growth given the UAE's strategic position as a global trade hub. Some studies based on different models have already been carried out to anticipate trade volumes detect emerging markets and industries and aid in investment and policy decision-making pertaining to trade in the UAE. These models have integrated advanced security protocols to ensure that the trade secrets and strategic insights remain confidential. They consider trade dynamics, industry diversification, and geopolitical factors to generate more tailored and accurate forecasts, for the nation.

Many studies have investigated the use of predictive analytics in trade forecasting to improve resource allocation (Singh & El-Kassar, 2019), pricing strategies (Shrivastava & Riaz, 2022), and inventory management for companies engaged in the UAE's trade sector (Al Mesfer, 2023). Incorporating security measures like encryption and access control ensures that this predictive intelligence is not compromised. Predictive models have proven to be tools for businesses enabling them to mitigate risks, boost profitability, and make informed trade decisions. Secure predictive analytics models play a critical role in this process, protecting trade secrets while enabling companies to anticipate market movements. By examining the trade data, observing market trends, and understanding customer behavior, these models provide valuable insights into upcoming trade patterns and trends. This information is particularly beneficial for investors, businesses, and policymakers, enabling them to optimize their trade-related endeavors. Consequently, nations like the UAE can gain from increased growth and enhanced competitiveness.

Over the past few decades, UAE has emerged as a rapidly advancing nation with a robust economy, largely due to its active trade sector encompassing imports and exports (Ewers & Madeeha, 2022). Ensuring this growth trajectory requires a secure trade environment where data and predictive insights remain protected from cyber threats and intellectual property theft. Numerous forecasts of trade patterns and trends contribute to the development of strategic economic planning and growth within the UAE. By facilitating informed decision-making on investments, pricing strategies, inventory management, and resource allocation, trade forecasting is indispensable. However, conventional trade forecasting methods often struggle to accurately forecast the intricate and ever-changing nature of global trade.

The realm of predictive analytics, utilizing the potential of machine learning and statistical modeling, has become a beacon of success. In recent times, predictive analytics has enabled policymakers and businesses to make informed decisions, utilizing historical trade data and advanced analytical methods to provide valuable insight into future trade dynamics. Despite the numerous advantages predictive analytics provide for trade forecasting, a certain amount of uncertainty is causing its true effectiveness and applicability.

Therefore, it is essential to bridge this gap in knowledge through an empirical study centered on the deployment of predictive analytics to enhance trade forecasting within the UAE. Such an investigation can shed light on the precision, dependability, and pragmatic use of predictive analytics techniques within the UAE's unique trade area. By evaluating the capabilities of predictive analytics models, weighing data accessibility and quality, and comprehending the skill set essential for seamless integration, this research embarks on a journey to enhance trade forecasting capabilities in the UAE.

The study examines three distinct objectives: Firstly, to determine if predictive analytics techniques were beneficial to the accuracy of UAE's trade forecasts while ensuring the security of the data used. Secondly, to determine the most suitable predictive analytics models for trade forecasting in the UAE's distinctive context that also adhere to the highest standards of data security. Thirdly, to calculate the Gross Domestic Product (GDP) of the UAE and compare it with the forecasted trade and with other developing countries while keeping all the data and predictive insights secure against unauthorized access.

This study utilizes historical trade data and various predictive analytics techniques to provide a quantitative approach. The performance of the predictive model is rigorously evaluated based on parameters such as accuracy, precision, and recall. Additionally, qualitative insights are obtained through interviews with trade forecasting experts, shedding light on the real-world implementation nuances and challenges encountered by predictive analytics in the UAE.

The results of this study are remarkable, resulting in a significant impact on the UAE's trade sector. The anticipated outcomes include enhanced decision-making acumen, refined resource allocation, and a higher competitive edge on the global stage. Equally important is the assurance of secure data handling, which upholds the integrity of the UAE's trade intelligence. In addition, the study's contribution reverberates in the academic field, revealing the nuances that influence the effectiveness of predictive analytics techniques in various trade forecasting scenarios, with a special emphasis on their security posture.

### 1.2 Statement of the Problem

The connection between gross domestic product (GDP) and microeconomic variables, particularly imports and exports, has been a topic of discussion. This connection was crucial for informed decision-making regarding investment, pricing, and resource allocation by the government and businesses in the United Arab Emirates (UAE). Ensuring the security of the economic data involved in such analyses was paramount, as this information could be a target for cyber threats aiming to undermine economic stability. Furthermore, predicting the future direction of UAE trade could have enabled stakeholders to anticipate and prepare for economic changes. The security of the forecasting models and the data they used was essential to prevent manipulation and ensure the integrity of predictions.

Although time series forecasting techniques had been commonly used to forecast economic indicators like GDP, it remained uncertain whether these techniques could reliably predict the long-term direction of UAE trade. Given the sensitivity of the data involved, the application of secure data processing methods and access controls was necessary to protect against unauthorized access and potential data breaches. Thus, this study aimed to address the following problem:

1. What was the connection between GDP and microeconomic variables, specifically imports and exports, in the UAE when GDP was calculated using the expenditure approach? The reliability of this connection depended on secure data collection and handling methods to ensure the accuracy of the GDP calculation.
2. Could time-series prediction models effectively forecast the long-term direction of UAE trade based on historical data? It was critical to secure the historical data and the predictive models against cyber-attacks to maintain trust in their long-term forecasts.

By addressing these questions, this research provided valuable insights into the factors that influenced the UAE's economy and informed decisions regarding resource allocation and investment. Furthermore, the study's findings contributed to the existing academic literature on the relationship between microeconomic variables and GDP as well as the efficacy of time series forecasting techniques for predicting trade patterns. while highlighting the importance of data security in economic research.

### 1.3 Research Questions

The problem statement gave rise to the following research questions, which guided the investigation and analysis within the study:

1. How did the imports and exports of the UAE evolve over time, providing a comprehensive understanding of the trade dynamics within the country?
2. What were the past import and export trends of developed countries that had significant commercial links with the UAE, enabling a comparative analysis of trade patterns in the region?
3. Which were the major trade affiliates of the UAE for mutual trade, highlighting the key countries or regions with significant trade relationships with the UAE?

In identifying these, data privacy measures were put in place to protect the interests and commercial confidentiality of the UAE and its trade partners.

4. What were the primary commodities that the UAE exported abroad, shedding light on the key sectors and industries that contributed to the country's trade balance?
5. How was the GDP for UAE collected based on the expenditure approach, elucidating the methodology employed to calculate the economic output of the country? Robust cybersecurity measures were essential to safeguard the collection and processing of economic data, ensuring its accuracy and reliability.

## 1.4 Research Objectives

1. To use the Long Short-Term Memory (LSTM) model to implement the regression and predictive analysis to assess the relationship between trade and UAE imports/exports. Cryptographically secure protocols will be used to safeguard the trade data during the analysis.
2. To utilize the selected algorithm for the prediction of UAE exports and imports under changing scenarios. Here, we can integrate cryptographic techniques such as data anonymization or homomorphic encryption to ensure the privacy of sensitive trade data while using the LSTM algorithm for predictions.
3. To calculate the GDP of the UAE based on consumption, expenditure, investment, and net exports data. Utilize secure data environments and ensure all GDP-related data is encrypted at rest to protect the confidentiality of economic indicators.
4. To compare the GDP of the UAE and other high-income countries.
5. To evaluate the effectiveness of the regression analysis in predicting the relationship between GDP and exports/imports and in predicting trends. Apply secure computation techniques to maintain data privacy during the regression analysis, ensuring that insights are derived from encrypted datasets without exposing sensitive economic data.
6. To identify the main factors that influence trade in the UAE.

7. To provide recommendations to improve the accuracy of trade forecasting in the UAE.

The study aimed to gain a thorough understanding of the historical patterns and trends in trade within the UAE and the countries where there is the most trade exchange by examining these research questions. The research results added to the body of knowledge on international trade and improved understanding of trade dynamics in the region by offering insightful information that influenced business and policy decisions. The integration of cryptographic techniques not only provides clarity on the protection of sensitive data but also highlights the commitment to ethical research practices that respect data privacy and security.

## 1.5 Relevant Literature

The literature review concentrates on studies pertinent to examining the connection between a nation's GDP and its imports and exports. The topic covered in this literature review is research done to attempt to predict trade directions using the LSTM model.

### *1.5.1 Economic Growth Indicators*

Trade relationships are an important factor for economic growth, and Gross Domestic Product (GDP) is an essential measure to assess a country's economic performance. Imports and exports are critical components of trade relationships, and they affect a country's balance of payments, economic growth, and international competitiveness. This literature review explores the relationship between trade relationships, GDP, imports, and exports.

Trade relationships refer to the economic and political relationships between countries that facilitate the exchange of goods, services, and capital. The extent and nature of trade relationships can vary between countries, and they can be influenced by various factors such as tariffs, trade agreements, and political stability. Studies have shown that countries with stronger trade relationships tend to have higher levels of economic growth. For example, research by Linnemann (1966) found that trade relationships were positively correlated with GDP growth. Furthermore, research by Dollar and Kraay (2003) demonstrated that an increase in trade relationships was associated with an increase in per capita income. Moreover, research has shown that there is a positive relationship between GDP and trade relationships. For example, research by Rodriguez and Rodrik (2000) found that countries with high levels of trade tend to have higher levels of GDP. Similarly, research by Frankel and Romer (2017) found that trade openness was positively associated with economic growth.

Imports and exports are a critical component of trade relationships, and they can have a significant impact on a country's balance of payments, economic growth, and international competitiveness. Imports refer to goods and services that are brought into a country, while exports refer to goods and services that are produced domestically and sold to other countries. Research has shown that there is a positive relationship between exports and economic growth. For example, research by Baldwin and Gu (2005) found that an increase in exports was associated with an increase in GDP. Similarly, research by Edwards (1998) found that countries with higher levels of exports tend to have higher levels of economic growth. On the other hand, imports can have a negative impact on a country's balance of payments and domestic industries. Research has shown that there is a negative relationship between imports and economic growth. For example, research by Lee et al. (2004) found that an increase in imports was associated with a decrease in GDP.

Frankel and Romer (2017) examined the two countries' bilateral trade. To gauge trade between the two countries, the authors employed the Trade Intensity Index (export and import):

Exports Intensity Index = (ABn / AB) / ((TI / (Tw - YZ)) Equation (1)

where, ABn = 1st country exports to 2nd country

AB = Total exports of 1st country

TI = 2nd country total imports

Tw = Total world imports

YZ = Total imports of 1st country

Import Intensity Index = (ABn / AB) / ((TE / (Tw - YZ)) Equation (2)

where, ABn = 1st country exports to 2nd country

AB = 1st country total imports

TE = 2nd country total exports

Tw = Total world exports

YZ = Total exports of 2nd country

Multiple regression approach was employed in the macroeconomic study for Bosnia and Herzegovina. This study evaluated the six independent variables to determine how macroeconomic factors (independent variables) impact gross domestic product (GDP); growth rate, unemployment, foreign direct investment (FDI), inflation, imports, and exports and (dependent variable). For their analysis, the authors utilized the following multiple regression formula:

$$Y=A_o+ A_1 Z_1+A_2 Z_2+A_3 Z_3+A_4 Z_4+A_5 Z_5+A_6 Z_6+\varepsilon \qquad \text{Equation (3)}$$

Their multiple linear regression model was presented as follows: GDP is a dependent variable and inflation, unemployment, growth rate, exports, imports, FDI are considered as independent variables. ε is used to reflect effects on GDP that are not caused by the independent variables.

The above analysis conducted by the author indicates that that 93.2% of changes in GDP can be explained by the independent variables. The researcher concluded that exports and FDI had the least impact on GDP, whereas imports have the highest impact.

### *1.5.2 Trade Forecasting*

The foundation of economic decision-making is trade forecasting, which leads countries, companies, and investors through the complex web of global trade. Accurate trade pattern forecasting gives businesses an advantage in navigating international markets as well as enabling policymakers to create effective economic strategies. The importance of accurate and forward-looking trade forecasting increases as the world becomes more interconnected and trade dynamics become more complex.

Predictive analytics is a transformative strategy that makes use of data-driven insights to predict future trends because of the fusion of conventional economic theories and cutting-edge technological advancements. Predictive analytics transcends traditional statistical methods by exposing hidden patterns, relationships, and potential disruptions in trade flows. It is frequently paired with its powerful counterpart, machine learning. Its ability to condense massive amounts of past and present trade data into usable forecasts represents a sea change in the field of trade analysis.

The complex interplay between macroeconomic forces and microeconomic behavior emerges as a central theme as we explore the world of trade forecasting and predictive analytics. The trajectory of international trade is influenced by factors such as GDP growth, inflation rates, geopolitical events, and consumer preferences. Making informed decisions at the national and organizational levels is made possible by having a nuanced understanding of the complex relationship between these variables and trade patterns.

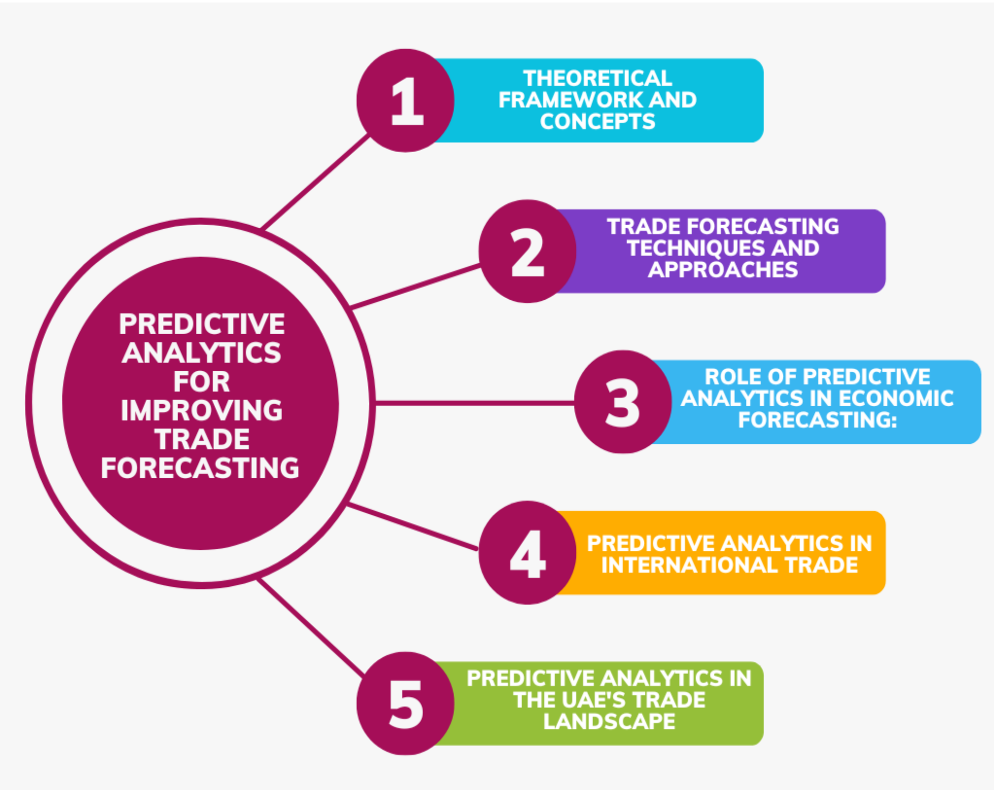



Figure 1: Classification of literature review

We explore the nuances of predictive analytics and its use in the context of the UAE as we search into the complexities of trade forecasting. Figure 1 shows how the literature review is classified into different categories to provide a comprehensive overview that how scientists are using predictive tools for economic forecasting. We aim to uncover the underlying dynamics that underlie trade patterns, solve the riddle of predictive analytics, and provide insightful contributions to the advancement of trade forecasting methodologies through empirical analysis and a meticulous evaluation of historical trade data. In order to improve the accuracy and the quality of our decisions in the area of forecasting UAE trade, we are entering into uncharted data-driven insights.

### *1.5.2 Theoretical Framework and Concepts*

The theoretical framework that underpins predictive analytics forms the bedrock upon which modern trade forecasting capabilities rest. Drawing from an amalgamation of established theories, models, and concepts, predictive analytics infuses innovation into trade forecasting methodologies, yielding enhanced accuracy and actionable insights. As we delve into the realm of predictive analytics' relevance to trade forecasting, this section navigates through key theoretical underpinnings while citing original research that has paved the path for its application.

Time series analysis, a cornerstone in economic modeling, establishes a temporal dimension to trade forecasting. The work of Geurts (1977) is emblematic in introducing Autoregressive Integrated Moving Average (ARIMA) models, offering a robust framework for capturing the intrinsic sequential dependencies within trade data. The integration of these techniques within predictive analytics lends temporal context to trade patterns, unveiling cyclical, seasonal, and trend-based fluctuations that impact cross-border exchanges (GEP, 1970).

Machine learning algorithms, influenced by advancements in computational capabilities, bring a paradigm shift to trade forecasting methodologies. Notably, the Random Forest algorithm, introduced by Breiman (2001), ushers in an ensemble approach that amalgamates numerous decision trees to predict trade patterns with improved accuracy and robustness. Kleemann and Abdulai (2013) exemplifies the integration of Random Forest in predicting trade volumes and highlighting influential predictors within a global trade context.

Regression analysis, a venerable statistical tool, finds renewed vigor in predictive analytics for trade forecasting. Building upon its traditional applications, regression analysis embraces the multivariate dimension of predictive analytics, enabling the assessment of how multiple variables collectively influence trade patterns. Noteworthy is the study by Javed et al. (2016), which employs regression analysis to explore the determinants of bilateral trade between the UAE and its trading partners.

Furthermore, concepts of pattern recognition and anomaly detection, hailing from the realm of artificial intelligence, enrich predictive analytics' ability to discern atypical trade behaviors that might indicate impending shifts. The pioneering work of Bartos et al. (2019) on detecting anomalies in time series data is emblematic of this concept's relevance, offering a mechanism to identify irregular trade occurrences that necessitate prompt attention.

In essence, the theoretical fabric interwoven with predictive analytics amalgamates temporal dynamics, computational prowess, and multivariate insight. Time series analysis, machine learning algorithms, regression analysis, and anomaly detection collectively scaffold predictive analytics, transforming trade forecasting from a static endeavor into a dynamic, data-driven discipline. Through the synthesis of these theories, predictive analytics emerges as a potent lens that illuminates the intricacies of trade patterns, unfurling a tapestry of insights that elevate the precision and efficacy of trade forecasting methodologies.

### *1.5.3 Trade Forecasting Techniques and Approaches*

The realm of trade forecasting encompasses a variety of techniques and approaches, each offering a unique opportunity to anticipate the intricate dynamics of global commerce. This section focuses on the diverse landscape of trade forecasting methodologies, from conventional methods to advanced predictive analytics, highlighting their evolution and real-world applications. Figure 2 shows the division of trade forecasting methods and techniques that are in use by the researchers in trade forecasting.

Table 1 shows the comparisons of different trade forecasting approaches and techniques from literature.

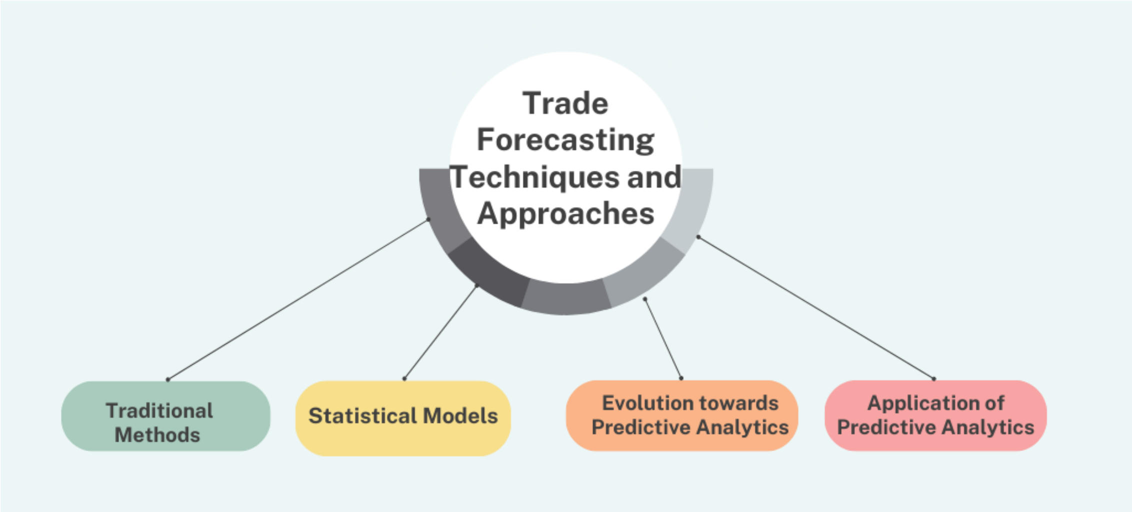


Figure 2: Trade forecasting methods

Table 1: Comparison of trade forecasting techniques and approaches

| Technique/Approach | Key Features | Application |
|---|---|---|
| Traditional Methods | Based on historical data patterns | Initial insights into trade trends |
| Statistical Models | Incorporates temporal dependencies and interrelationships | Captures dynamic interactions among trade variables |
| Predictive Analytics | Utilizes machine learning, deep learning, and computational power | Enhances forecasting accuracy and captures long-term dependencies |
| Application of Predictive Analytics | Applies predictive models to forecast trade volumes and patterns | Improved forecasting accuracy in various trade contexts |

#### 1.5.3.1 Traditional Methods

Traditional trade forecasting methods have long served as the cornerstone of economic analysis. Methods like moving averages, exponential smoothing, and linear regression have provided initial insights into trade trends by extrapolating historical data patterns. While offering a rudimentary understanding of trade dynamics, these methods often fall short in capturing the intricacies of modern trade patterns and their underlying drivers.

#### 1.5.3.2 Statistical Models

Statistical models, such as autoregressive integrated moving average (ARIMA) and vector autoregression (VAR), introduced a more sophisticated framework by accounting for temporal dependencies and interrelationships among trade variables. ARIMA, championed by 1. Geurts, M. (1977), leverages time series analysis to capture the sequential patterns in trade data, while VAR extends the analysis to encompass the dynamic interplay among multiple trade variables.

#### 1.5.3.3 Evolution Towards Predictive Analytics

The emergence of predictive analytics marked a transformative shift in trade forecasting methodologies. Predictive analytics, underpinned by machine learning algorithms and advanced computational capabilities, redefined the boundaries of trade analysis. Notably, the Long Short-Term Memory (LSTM) model within the deep learning paradigm enabled the incorporation of sequential patterns into trade forecasting. LSTM, introduced by Hochreiter and Schmidhuber (1997), possesses a unique memory-enhanced architecture that excels at capturing long-term dependencies in time series data, making it particularly apt for forecasting trade patterns.

##### 1.5.3.3.1 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a type of Recurrent Neural Network (RNN) that has been widely used in various applications, including time series forecasting. This literature review explores the use of LSTM for trade forecasting, with a focus on its advantages, limitations, and empirical evidence. LSTM has several advantages for trade forecasting. First, it can capture long-term dependencies in time series data, which is essential for trade forecasting because trade patterns are often affected by economic and political factors that may take time to unfold. Second, LSTM can handle non-linear relationships between input and output variables, which is useful for predicting trade patterns that may be influenced by complex and interrelated factors. Finally, LSTM can learn from historical data to generate accurate predictions for future trade patterns. Despite its advantages, LSTM has some limitations for trade forecasting. First, LSTM requires large amounts of historical data to learn from, and trade data may be limited or incomplete for some countries or regions. Second, LSTM may struggle to generalize to unseen data, and its predictions may be less accurate for countries or regions that have different trade patterns from those in the training data. Finally, LSTM requires careful tuning of hyperparameters, and its performance may be sensitive to the choice of hyperparameters. Several studies have explored the use of LSTM for trade forecasting. For example, a study by Wang et al. (2019) used LSTM to predict China's trade with the United States and found that LSTM outperformed traditional time series models. Similarly, a study by Rasoulinezhad et al. (2020) used LSTM to predict the trade balance of Iran and found that LSTM improved prediction accuracy compared to traditional time series models. Another study by Chen et al. (2019) used LSTM to predict China's exports to the United States during the trade war between the two countries and found that LSTM was able to capture the complex and dynamic relationships between trade and political factors. Finally, a study by Bouri et al. (2020) used LSTM to predict the direction of trade for five major economies and found that LSTM outperformed traditional statistical models. Hu et al. (2021) used an LSTM model to forecast the monthly trade volume between China and the United States. Their study showed that the LSTM model outperformed traditional forecasting models in terms of prediction accuracy. Wu et al. (2020) used an LSTM model to forecast China's trade with the United States and Japan. Their results showed that the LSTM model had better prediction accuracy than traditional forecasting models. Li et al. (2019) used an LSTM model to forecast the volume of China's imports and exports.

Their results showed that the LSTM model outperformed traditional models in terms of prediction accuracy and was able to capture the non-linear relationships in the data. Zhang et al. (2020) used an LSTM model to predict the import and export volume of China's agricultural products. Their results showed that the LSTM model had better prediction accuracy than traditional models. Ma et al. (2019) used an LSTM model to forecast the import and export volume of China's liquefied natural gas. Their results showed that the LSTM model outperformed traditional models in terms of prediction accuracy. These studies suggest that LSTM is a promising tool for trade forecasting due to its ability to capture long-term dependencies and handle non-linear relationships in the data. LSTM has been shown to outperform traditional forecasting models in several cases. However, further research is needed to test the generalizability of the model across different trade patterns.

#### *1.5.3.4 Application of Predictive Analytics*

Recent studies have demonstrated the potential of predictive analytics to revolutionize trade forecasting. Balaji et al. (2018) harnessed machine learning techniques, including LSTM, to predict the trade volume between China and its trading partners, showcasing improved forecasting accuracy compared to traditional methods (Balaji et al., 2018). Similarly, Dumor and Yao (2019) employed predictive analytics to anticipate trade flows within the Belt and Road Initiative, elucidating the model's capacity to forecast trade dynamics across diverse regions.

The evolution of trade forecasting techniques has led to a transition from traditional methods to advanced predictive analytics, resulting in a shift towards more accurate, dynamic, and insights-driven predictions. The integration of machine learning algorithms and deep learning architectures such as LSTM presents a promising opportunity for trade analysts to gain a deeper understanding of trade patterns and anticipate their evolution on a global scale.

The integration of predictive analytics into economic forecasting has ushered in a new era of insights-driven decision-making. This section delves into the transformative role of predictive analytics in anticipating critical macroeconomic indicators, such as GDP, inflation, and more. Moreover, it examines noteworthy studies that have harnessed predictive analytics to forecast economic trends, shedding light on its implications for informed policy formulation.

*1.5.4 Role of Predictive Analytics in Economic Forecasting*

Predictive analytics transcends traditional econometric approaches by leveraging advanced algorithms and vast data repositories. By discerning intricate patterns within historical and real-time data, predictive analytics augments the accuracy and timeliness of economic predictions. Its application extends to pivotal macroeconomic indicators, including Gross Domestic Product (GDP) growth, inflation rates, and unemployment levels, thereby equipping policymakers and stakeholders with crucial foresight.

Table 2: Studies utilizing predictive analytics in economic forecasting

| Study | Predictive Analytics Approach | Economic Indicators Forecasted | Implications for Policymaking |
|---|---|---|---|
| Mishkin (1998) | Neural Networks | Inflation | Enhanced inflation prediction |
| Giannone et al. (2008) | Dynamic Factor Models | Industrial Production | Improved industrial production forecasting |
| Peersman, G. (2004) | Bayesian VAR | GDP growth | Accurate GDP growth forecasts |
| Koop et al. (2019) | Mixed-Frequency Models | Unemployment Rate | Timely unemployment rate forecasts |
| Barbaglia & Manzan (2023) | Machine Learning and Dynamic Factor Models | Economic Sentiment | Enhanced sentiment-based economic forecasting |

The aforementioned studies shown in Table 2 collectively underscore the efficacy of predictive analytics in economic forecasting. Estrella and Mishkin (1998) demonstrated the viability of neural networks in enhancing inflation predictions (Estrella & Mishkin, 1998). Giannone et al. (2008) showcased the utility of dynamic factor models in refining industrial production forecasts. Peersman (2004) harnessed Bayesian VAR models for accurate GDP growth predictions. Koop et al. (2019) employed mixed-frequency models to achieve timely unemployment rate forecasts. Furthermore, Barbaglia and Manzan (2023) illustrated the potential of machine learning and dynamic factor models in sentiment-based economic forecasting.

In essence, predictive analytics empowers economic forecasters with an arsenal of tools to unravel the intricacies of economic trends. By extracting meaningful insights from vast and diverse datasets, predictive analytics enriches the accuracy, granularity, and timeliness of economic predictions, ushering in a data-driven paradigm that holds profound implications for policy-making and strategic decision-making.

### *1.5.5 Predictive Analytics in International Trade*

International trade is one area where predictive analytics has found a strong application due to its aptitude for identifying subtle patterns within large, complex datasets. The studies in this section that have used predictive models to navigate the complex world of cross-border trade delve into the specific uses of predictive analytics in international trade. These applications include predicting trade effects in the face of economic shocks, analyzing the effects of trade agreements, and anticipating changes in trade patterns.

### *1.5.6 Anticipating Changes in Trade Patterns*

Predictive analytics serves as a beacon for trade analysts seeking to forecast shifts in trade patterns. In the work of Nabipour et al. (2020), machine learning models were employed to predict export market diversification, enabling nations to foresee potential shifts in their export destinations and strategize accordingly. By utilizing historical trade data, these models reveal subtle changes in market preferences, enabling nations to proactively adapt their trade strategies.

### *1.5.7 Analyzing Trade Agreement Impacts*

Predictive analytics explores the complex nature of trade agreements and illuminates their potential effects. Raza et al. (2016) utilized machine learning techniques to analyze the impact of trade agreements on Nigeria's trade flows, providing insights into the dynamics of trade after agreements. These analyses provide decision-makers with the ability to evaluate the success of trade agreements and adjust their strategies to maximize trade advantages.

### *1.5.8 Predicting Effects of Economic Shocks on Trade*

Predictive analytics emerges as a shield against economic uncertainties by offering predictions of trade effects amid shocks. The study by Glikson and Woolley (2020) showcased how machine learning models can predict the effects of tariff changes on trade flows, enabling governments and businesses to prepare for potential disruptions. These predictive insights equip stakeholders with foresight, enabling agile responses to safeguard trade interests. Table 3 shows the applications of predictive insights in the international trade.

Table 3: Applications of predictive analytics in international trade

| Study | Predictive Analytics Approach | Application | Implications |
|---|---|---|---|
| Nabipour et al. (2020) | Deep Learning Models | Export Market Diversification | Proactive adaptation of trade strategies |
| Raza et al. (2016) | Machine Learning Techniques | Impact of Trade Agreements | Informed policy-making |
| Glikson & Woolley (2020)) | Machine Learning Models | Effects of Tariff Changes on Trade Flows | Preparedness for economic disruptions |

The highlighted studies collectively underscore the potency of predictive analytics in international trade, unveiling its role in shaping strategic decisions in an era of global economic intricacies. The capacity to anticipate trade pattern shifts, assess trade agreement impacts, and predict trade effects amidst economic shocks lends an unparalleled edge to stakeholders navigating the complex terrain of international trade.

### *1.5.9 Predictive Analytics in the UAE's Trade Landscape*

The use of predictive analytics in the context of the United Arab Emirates (UAE) trade landscape is a dynamic interplay of cutting-edge technology and economic foresight. This section investigates studies that have explored the field of predictive analytics to shed light on the complex dimensions of trade dynamics in the UAE. Researchers have examined historical trade data, predicted future trade patterns, and improved the precision of trade forecasts within the unique economic context of the UAE by using predictive models. In Table 4, the exploration of predictive analysis of studies is shown regarding UAE trade forecasting.

Table 4: Exploration of predictive analytics studies in UAE trade forecasting

| Study | Predictive Analytics Approach | Application | Key Findings |
|---|---|---|---|
| Worku & Rao (2018) | Artificial Neural Networks | Non-Oil Trade Forecasting | Improved prediction accuracy |
| Ismail et al. (2020) | ARIMA Models and Machine Learning Techniques | Foreign Trade Forecasting | Enhanced trade forecasts for policy-making |
| Sen & Dutta (2022) | Long Short-Term Memory (LSTM) Model | Dubai's Non-Oil Foreign Trade Forecasting | LSTM-based model outperforms baseline |
| Al-Mansoori et al. (2018) | Artificial Neural Networks | Non-Oil Trade Forecasting | Improved prediction accuracy |

The studies presented here collectively underscore the transformative potential of predictive analytics in elucidating the UAE's trade landscape. By leveraging predictive models and data-driven insights, researchers have enriched the accuracy, granularity, and timeliness of trade forecasts, thus enabling policymakers and stakeholders to navigate the intricacies of the UAE's trade dynamics with a heightened degree of confidence.

### *1.5.10 Challenges and Limitations*

While predictive analytics offers unprecedented potential to revolutionize trade forecasting, it is not without its challenges and limitations. As researchers delve into this dynamic realm, they must navigate a complex landscape marked by intricacies related to data quality, model accuracy, interpretability, and potential biases. Awareness of these challenges is crucial for conducting accurate and informed trade forecasts. Table 6 presents challenges and limitations in Predictive Analytics for Trade Forecasting.

#### *1.5.10.1 Data Privacy and Security*

To improve the accuracy and dependability of trade forecasting, in the UAE the use of encryption is crucial for protecting economic data. This cryptographic technique enables calculations to be performed on encrypted data allowing LSTM predictive models to analyze and predict trade patterns without decrypting the information. As a result all trade data, including imports, exports and detailed GDP components remains secure throughout the analysis process guarding against access and potential data breaches. By utilizing encryption the UAE ensures that its economic activities remain confidential while benefiting from predictive analytics to inform trade decisions and strategies. This strengthens its reputation as an forward thinking participant, in trade.

#### *1.5.10.2 Data Quality and Availability*

Predictive analytics heavily relies on robust, accurate, and comprehensive data. However, trade data can be fragmented, inconsistent, and subject to reporting delays. Data quality issues can undermine the efficacy of predictive models, leading to inaccurate forecasts. Researchers must grapple with missing data, outliers, and discrepancies, which can introduce noise and affect the model's performance.

#### *1.5.10.3 Model Accuracy and Generalization*

The accuracy of predictive models hinges on their ability to generalize beyond the training data. Overfitting—an issue where models capture noise instead of patterns—can compromise forecasting accuracy. Striking the right balance between model complexity and simplicity is a delicate task, as overly complex models may perform well on training data but falter in real-world scenarios.

*1.5.10.4 Interpretability and Transparency*

Sophisticated predictive models, such as deep learning architectures, can be challenging to interpret. The "black-box" nature of some models limits their transparency, making it difficult to discern the underlying factors driving forecasts. Researchers may face resistance from stakeholders who demand comprehensible explanations for forecast outcomes.

*1.5.10.5 Potential Biases and Assumptions*

Predictive models are not immune to biases that may exist in historical trade data. Biases can arise from various sources, such as sampling methods, measurement errors, and inherent data inequalities. Unaddressed biases can lead to skewed forecasts that fail to capture the true trade dynamics.

*1.5.10.6 Dynamic Nature of Trade*

The trade landscape is highly dynamic, influenced by geopolitical shifts, economic policies, and global events. Predictive models may struggle to adapt swiftly to unforeseen changes, especially when these shifts deviate from historical patterns.

Table 5: Challenges and limitations in predictive analytics for trade forecasting

| Challenge | Description | Implications |
|---|---|---|
| Data Quality and Availability | Fragmented, inconsistent, and delayed data can compromise model performance | Inaccurate forecasts and reduced confidence in predictions |
| Model Accuracy and Generalization | Overfitting and poor generalization can impact forecast reliability | Unreliable forecasts in real-world scenarios |
| Interpretability and Transparency | Complex models may lack transparency and hinder understanding | Resistance from stakeholders and limited insights |
| Potential Biases and Assumptions | Biases in historical data can lead to skewed forecasts | Misrepresentation of trade dynamics |
| Dynamic Nature of Trade | Rapidly changing trade landscape can challenge model adaptation | Inability to capture unforeseen changes |

In navigating these challenges, researchers must adopt a holistic approach that involves data preprocessing, careful model selection, validation techniques, and a deep understanding of the trade context. Recognizing and addressing these limitations is pivotal to harnessing the full potential of predictive analytics for trade forecasting, ultimately enabling more accurate and informed decision-making.

# Chapter 2: Methodology

In this study, we harnessed the predictive capabilities of the Long Short-Term Memory (LSTM) algorithm, a specific type of recurrent neural network (RNN). LSTMs excel in analyzing time-series data, a quality particularly valuable for forecasting trade dynamics such as volumes and values, owing to their capacity to discern intricate temporal relationships within sequential datasets.

## 2.1 Development of the LSTM Model

Our LSTM model was structured with careful consideration for the predictive analysis: We have the following setup for our LSTM model:

### *2.1.1 First LSTM Layer (Input Layer)*

The first LSTM layer is configured with 50 units, and it utilizes the Rectified Linear Unit (RELU) activation function. This layer serves as the input layer and is responsible for processing the sequential input data.

### *2.1.2 Second LSTM Layer*

This layer also consists 50 units with RELU activation and returns sequences, it distinct from the first layer as it is operated as an intermediary tier. This allows the model to further capture more complex temporal patterns in the data.

### *2.1.3 Third LSTM Layer*

Comprises 50 units with RELU activation but doesn't return sequences. This layer aggregates the information learned from the previous layers into a condensed representation.

### *2.1.4 Dense Layers*

Two Dense layers follow the LSTM layers. The first Dense layer has 25 units, and the second Dense layer contains a single unit (output layer). These Dense layers are fully connected layers responsible for generating the final output of the model. They help transform the LSTM layer's output into a prediction or forecast.

### 2.2 Optimization of the LSTM

To enhance the model's performance, we employed the Adam optimizer, known for its efficiency in guiding deep learning models toward optimal minima. Concurrently, we adopted the mean squared error (MSE) loss function, a particularly suitable choice for LSTM-based forecasting tasks. The MSE quantifies the average squared deviation between predicted values and actual observations, aligning with the essence of forecasting precision.

### 2.3 Model Evaluation

The model evaluation phase involved assessing its predictive efficacy through comparisons with previously unseen test data. This procedure guards against overfitting, ensuring the model's generalization ability to novel data.

### 2.4 Hyperparameter Tuning

Hyperparameters, critical configuration settings of the LSTM model, underwent meticulous fine-tuning. These included hidden unit count, layer depth, optimization algorithm, and loss function. Multiple techniques, encompassing grid and random search, were employed in the process.

### 2.5 Model Training

The training regimen of the model followed a systematic sequence:

#### *2.5.1 Initialization*

Commencing with random weight assignment, the model began its learning journey. The complete steps for the training of LSTM model are shown in Figure 3.

#### *2.5.2 Training Data Integration*

The model was exposed to comprehensive training data, and its internal weights were adjusted iteratively to minimize the loss function.

*2.5.3 Evaluation*

Subsequently, the model underwent evaluation using an independent test dataset, with performance metrics recorded.

*2.5.4 Iterative Refinement*

Steps 2 and 3 were repeated iteratively until the model exhibited convergence or until a predefined number of training iterations transpired.

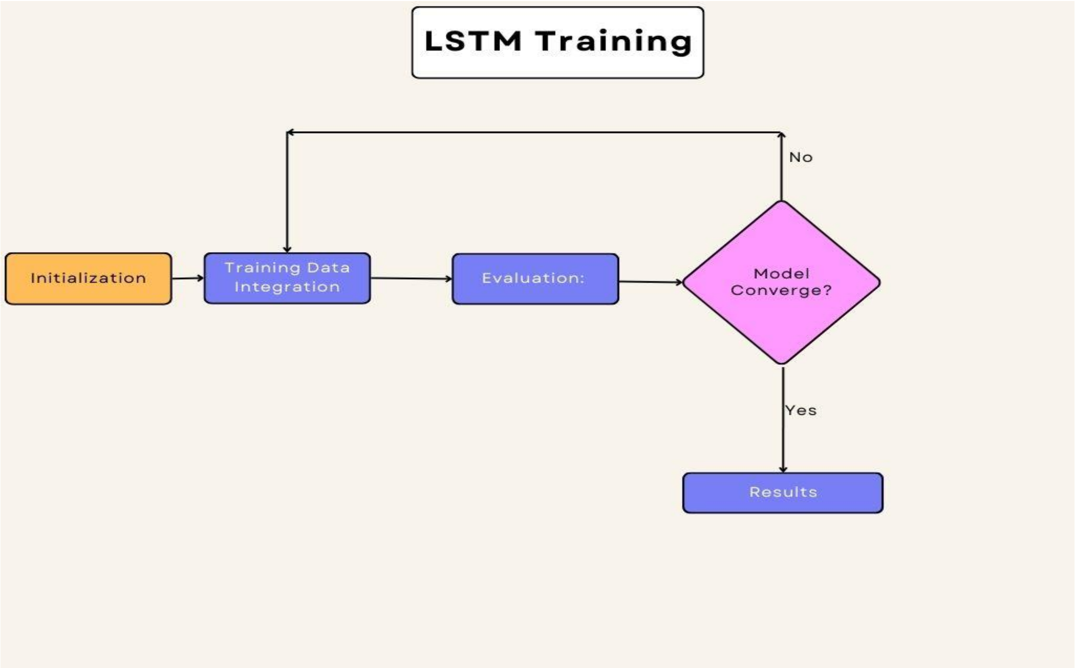



Figure 3: Training flow chart of LSTM model

*2.5.5 Performance Assessment*

Model evaluation entailed a quantitative assessment, involving a comparison between predicted values and actual values. The mean squared error (MSE) served as the quantitative measure, with reduced MSE values indicative of heightened predictive accuracy.

**2.6 LSTM Model for Trade Analysis (Imports/Exports)**

The trade analysis conducted for this study focused on the UAE's import and export patterns with various nations to provide insights into the dynamics of global trade. A strong data analysis tool called LSTM, a particular kind of recurrent neural network (RNN) was used to accomplish this.

Following libraries were imported:

- `pandas` for data manipulation
- `numpy` for numerical computation
- `matplotlib.pyplot` and `seaborn` for data visualization
- `sklearn.preprocessing` for data preprocessing
- `keras.models` and `keras.layers` for building and training the LSTM model
- `os` for accessing files and directories.

Our research framework benefited greatly from the use of the Pandas libraries, which made it easier to manage the UAE's trade dataset and provide data for the LSTM model training. Our study's key components—the resulting visualizations and LSTM model training offered priceless insights into the trade dynamics and economic indicators of the UAE.

### 2.7 Dataset Acquisition and Data Cleaning

In the data acquisition phase of this thesis, essential datasets for the analysis of trade dynamics in the United Arab Emirates (UAE) and GDP calculations were gathered from reliable sources. Import and export data for the UAE, as well as selected developed countries, were collected from various websites offering comprehensive trade statistics. Additionally, GDP figures for the UAE and the chosen developed nations were obtained, serving as critical metrics to assess the economic impact of trade activities. The selection of data sources was based on their credibility, relevance, and availability of historical data, ensuring the robustness and accuracy of the analysis.

The data-cleaning process is a crucial and essential part of the research process. It forms the basis for the accuracy and dependability of our LSTM model and subsequent analyses. In this regard, the following fundamental data-cleaning procedures were carefully carried out.

#### *2.7.1 Row Deletion with NaN Values*

In our dataset, we systematically removed any rows that contained NaN (Not-a-Number) values. This step is crucial because it makes sure that none of the information in our data is missing or incomplete. Our LSTM model relies on a large and coherent dataset, so any omissions could seriously impair its ability to learn and predict.

#### *2.7.2 Column Renaming*

The process of renaming columns is not just a matter of nomenclature; it is a deliberate attempt to improve the readability and comprehension of data. We can precisely identify and comprehend the variables being taken into consideration thanks to descriptive and well-defined column names. This step is important to take to make sure that our model can accurately capture the subtleties of the data.

#### *2.7.3 Streamlining Column Names*

Column names can be made simpler to further streamline the data. Clear and consistent column labels encourage uniformity and facilitate easy referencing throughout the analysis. This helps to make our visualizations and results more understandable as well as to train our LSTM model.

#### *2.7.4 Elimination of Completely NaN Columns and Rows*

Completely NaN columns and rows are redundant and don't provide any useful information. Their presence can introduce noise to the data, which could result in incorrect inferences. Therefore, getting rid of them is essential to maintaining data integrity.

#### *2.7.5 Index Resetting*

Resetting the index ensures that the data are organized coherently and sequentially. This is necessary to preserve the dataset's temporal and relational characteristics, which are especially important in time-series analysis, as is the case with our LSTM model.

Each of these data-cleaning procedures significantly raises the standard and dependability of our research. They work together to strengthen our LSTM model's accuracy and robustness, which strengthens the validity of our findings and conclusions.

This methodical approach highlights our dedication to scientific integrity and rigor in our examination of the trade dynamics and economic indicators of the UAE.

### *2.7.6 Data Extracting*

In this first step, we focus on extracting and isolating the data related to total exports to a particular country. This is a key element of our analysis because it allows us to focus on a particular aspect of trade dynamics. We can effectively train our LSTM model to recognize and predict patterns in the export behavior of the UAE with respect to specific countries by limiting our focus in this way.

### *2.7.7 Data Normalization*

To standardize the data and bring it to a common scale, normalization is a crucial preprocessing step. When working with numerical features that may have different ranges, this is crucial. We ensure that all input variables are treated equally by the model by normalizing the data. This step helps the LSTM remain stable and converge during training by ensuring that no single variable has an overwhelming influence on the learning process.

### *2.7.8 Data Splitting*

We divide our dataset for model evaluation, following best practices to prevent overfitting. Initially, 70% of the data is allocated for training, and 30% for testing. From the training data, we further allocate 90% for training, and the remaining 10% for validation. This multi-tiered division allows us to gauge the model's performance on unseen data effectively and independently validate its predictive capabilities.

## 2.8 Function of Dataset Creation for LSTM

For LSTM modeling, it is essential to create a suitable dataset structure. We create a function that makes it easier to arrange our data into batches or sequences that are appropriate for LSTM input. This function sets up the data into input-output pairs so that the LSTM can successfully learn sequential patterns. The model can learn and predict trends over time because each input sequence has a corresponding target or output sequence.

## 2.9 Cryptographic Enhancement for Data Security

To ensure the security of the data we incorporated cutting edge methods. We employed encryption on the datasets before conducting analysis allowing our LSTM model to perform calculations, on encrypted data while keeping its confidentiality intact. This encryption method guaranteed that our model could extract insights from datasets ensuring the preservation of data privacy and integrity, throughout the forecasting process. The seamless integration of cryptographic security within the LSTM's operational framework set a new precedent for conducting sensitive economic analyses without exposing the data to potential vulnerabilities.

### *2.9.1 Homomorphic Encryption*

Homomorphic encryption is a cryptographic technique that allows calculations to be conducted on encrypted data, producing an encrypted output that, when decrypted, yields the same result as if the operations were performed on the original unencrypted data. This implies that information can be encoded and transmitted to a third party for analysis without ever revealing the original data. The third party has the capability to carry out the required calculations and provide the outcomes in an encrypted format, which can only be decrypted and understood by the original data owner. Homomorphic encryption enables the secure analysis of confidential trade data in the realm of predictive analytics, especially in sensitive areas such as trade forecasting. This ensures that companies and governments can take advantage of advanced data analytics while maintaining the highest standards of data privacy. In an age where data breaches pose a substantial threat, this tool serves as a potent means of safeguarding data privacy. It facilitates secure calculations in the cloud while keeping privacy.

## 2.10 LSTM Model Preparation and Prediction

A python code was used for the preparation and prediction of LSTM model. The first line of code, train_size = int(len(scaled_data) * 0.7), defines the training set size as 70% of the total data. The next two lines of code, train, test = scaled_data[0:train_size, :], scaled_data[train_size:len(scaled_data), :], split the data into the training set and the test set.

The next five lines of code, scikit-learn's TimeSeriesSplit function to conduct time series cross-validation. In this specific case, the code is configured to perform 10 splits. Within a loop, the data is divided into training and testing subsets, preserving the temporal order of the data. The 'train_index' and 'test_index' variables capture the indices of these subsets. This approach enables robust model evaluation on time series data, providing a series of train-test sets for assessing predictive accuracy across different time periods, and likely stores the root mean squared error values in the 'rmse' list for each fold during cross-validation.

The LSTM model can then be trained on the training set. The predictions of the model can then be evaluated on the test set.

We have used Keras library to define and configure a neural network model. It starts by importing necessary components, including LSTM and Dense layers, and the Sequential model. A Sequential model represents a linear stack of layers, where data flows sequentially from one layer to the next.

The model is initialized with the Sequential() function. It then incorporates three LSTM layers, each containing 50 units, activated by the rectified linear unit (ReLU) function. The use of return_sequences=True in the first two LSTM layers signifies that these layers return the output as sequences, which is often necessary when stacking multiple LSTM layers.

Following the LSTM layers, two Dense layers are added to the model. The first Dense layer has 25 units, and the final layer has just one unit. Dense layers are fully connected layers, and the last layer with one unit is commonly used for regression tasks.

The model is compiled using the mean squared error (MSE) loss function and the Adam optimizer, which are standard choices for regression problems. Once the model is configured, it can be used for training and making predictions on your data.

A model fitting code was employed for model training, particularly in the context of deep learning using the Keras library. The training process involves iteratively optimizing the model's parameters to learn patterns from the provided training data. The training dataset consists of input data (xtrain) and the corresponding target outputs (ytrain) that the model aims to predict. With 200 training epochs, the model will undergo multiple passes through the training data, adjusting its weights to minimize the prediction error. A batch size of 1 indicates that the model updates its parameters after processing each individual data point, resembling stochastic gradient descent. The training process will produce updates on the training progress (verbosity set to 1), and data shuffling is disabled, meaning the order of the training data remains constant during training. Overall, this code initiates the essential training phase, enabling the model to learn from the training dataset and improve its predictive capabilities.

The code "ypred = model.predict(xtrain)" is a simple and crucial step in machine learning. Here, a pre-trained model takes the input data, xtrain, and produces predictions, which are stored in the variable ypred. These predictions are the model's estimates based on the input data and can be used for various tasks such as making forecasts or assessments.Similar to the previous line of code, this one makes predictions using the trained LSTM model on the testing dataset (X_test). The X_test dataset serves as an independent evaluation set and contains data that the model has not seen before. The model's ability to generalize and produce precise forecasts for unforeseen data is evaluated through predictions on this dataset.

To integrate cryptographic techniques with the predictive modeling in Python, we would use encryption to secure the data before making predictions, and then decrypt the predictions. This process would require a homomorphic encryption scheme that allows computations to be performed on encrypted data. We need to import Pyfhel, PyPtxt, PyCtxt from Pyfhel package. Here, is the encryption part code representation:

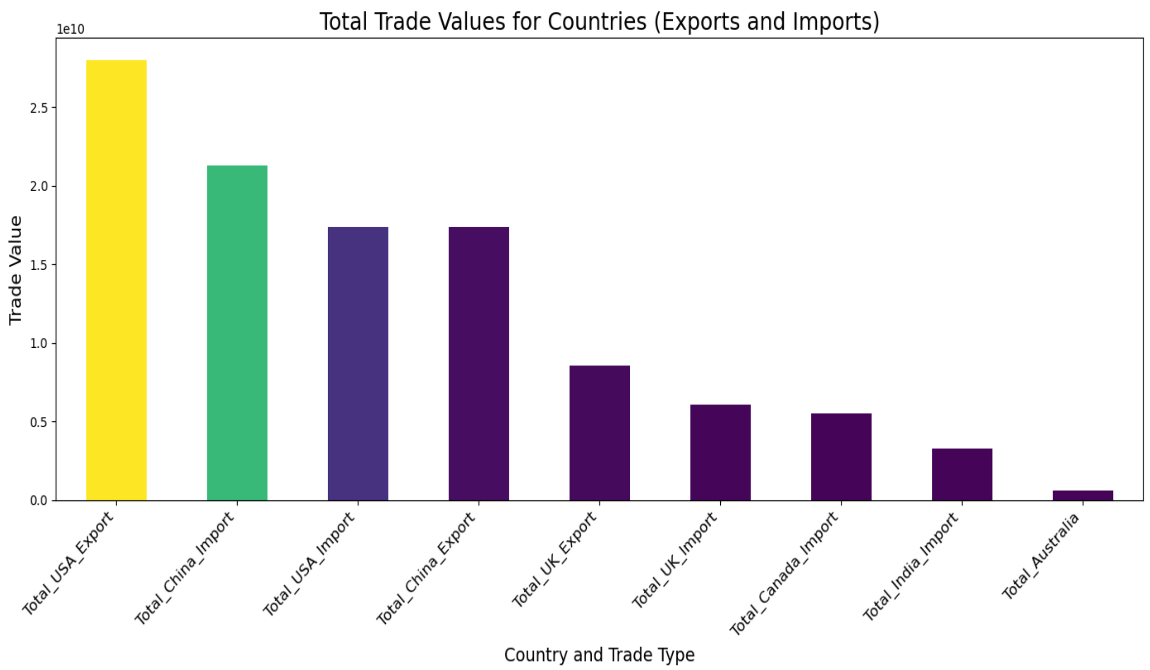
Initialize the Pyfhel object and HE = Pyfhel(), homomorphic encryption. Generate key using HE.keyGen(). For the input data xtrain for the model in plaintext, the encrypted data will be encrypted_xtrain = [HE.encryptFrac(x) for x in xtrain]. Here, the `model.predict()` method would have to be adapted to work with encrypted data .The encrypted test data using the public key is ‘xtest_encrypted’. Predictions with an LSTM model that is equipped to handle encrypted data. This requires the model to be specifically designed or adapted for working with homomorphic encryption libraries ypred_encrypted = [model.predict(x) for x in xtest_encrypted]. Decrypt the results using the private key 'secret_key' would typically be held by the client who needs to see the results. ypred = [y.decrypt(secret_key) for y in ypred_encrypted]. 'ypred' now contains the decrypted predictions

Transforming normalized values into original scale is very important as it transforms normalized values into their original scale. Input features and target variables are frequently scaled to aid in model training and convergence. However, it's important to deliver results in a format that is comprehensible and matches the units of the original data when presenting the model's predictions to stakeholders or users. It is possible to present the results in a way that is more significant and clearer by converting the predictions back to their original scale. The working of this code snippet is given below.

# Chapter 3: Experimentations and Results

## 3.1 Comparison of Imports and Exports

Comparing exports and imports is a crucial part of the analysis carried out in this study. The bar graph shown in Figure 4 gives a clear and insightful depiction of the United Arab Emirates' (UAE) trade relations with many important countries, illuminating export and import values. Nine bars make up this graphic representation, each of which is significant in relation to the UAE's international trade. The bars are set up in descending order of value, with the shortest bar denoting the lowest trade value and the tallest bar representing the highest.




*(*All units are in Thousands USD)*

Figure 4: Total trade values of imports and exports for countries and UAE

The United States is represented by the graph's tallest bar, making it the top export destination for the UAE. This large bar emphasizes the substantial value of goods exported from the UAE to the USA, highlighting the strong trade ties between these two countries. We have another large bar at the opposite end that represents China as the UAE's main importer. This bar highlights the sizeable amount of merchandise imported from China into the United Arab Emirates, underscoring the crucial contribution China makes to the UAE's domestic market. The value of imports from the USA is shown in the third bar. It represents a sizable amount of American goods being imported into the UAE, even though it is not as tall as the export bar to the USA.

Despite being shorter than the import from China, the fourth bar shows an important amount of goods exported from the UAE to China. The UAE's ability to export to the Chinese market is demonstrated by this. The value of goods exported from the UAE to the UK is shown in the fifth bar. It displays the UAE's presence in the UK market despite not being as tall as the top bars. The imports from the UK into the UAE are shown in the sixth bar. It alludes to the quantity of merchandise arriving from the UK in the UAE. Even though it is not as tall as some of the earlier bars, the seventh bar shows the amount of imports from Canada into the UAE. The eighth bar gives information about trade relations with India by showing imports from India into the UAE. The value of goods exported from the UAE to Australia is represented by the ninth and shortest bar in the graph. Even though it is the least valuable of the bars, it still shows trade connections with Australia.

### 3.2 Trade Imbalance

With China as a major import partner and the USA as a significant export destination, there is a significant difference in the height of the bars between imports from China and exports to the USA.

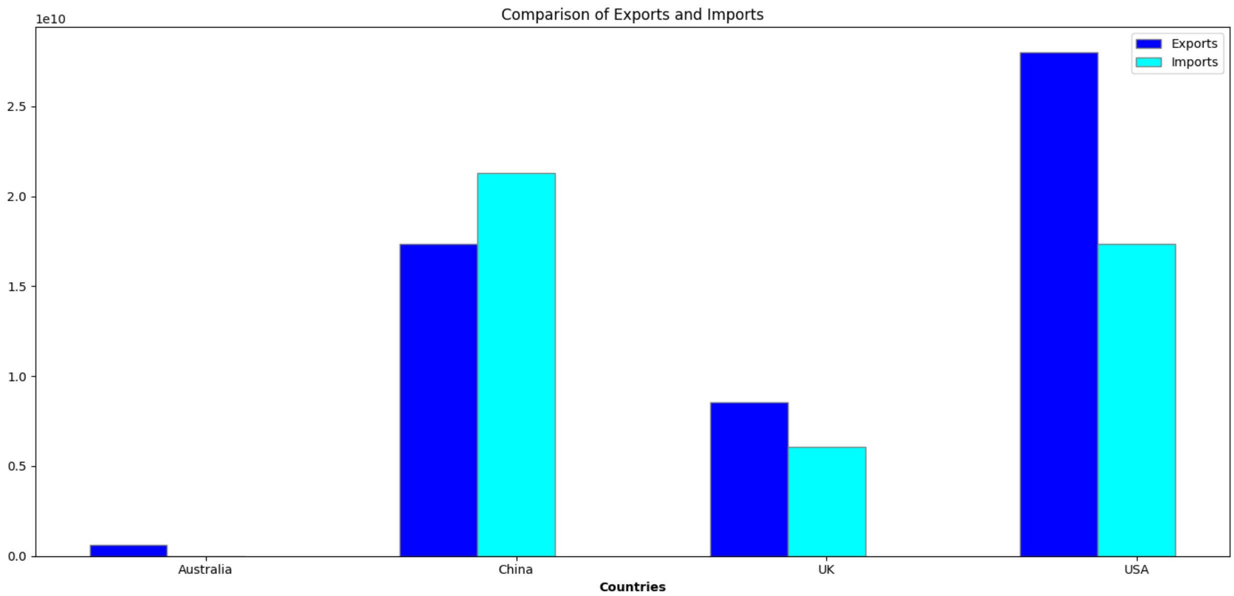
### 3.3 Diverse Trade Relationships

The graph highlights the UAE's diverse trade relationships, highlighting the country's significant imports and exports to and from a number of nations, including the USA, China, the UK, Canada, and India.

### 3.4 Trade Expansion Potential

Trade Growth prospects the export bars of the UK, Australia, and other countries show areas where the UAE can expand and diversify its export markets.

The trends seen in the previous Figure are corroborated in Figure 5 below, which compares the UAE's imports and exports with its top trading partners. This visualization confirms important findings and offers additional insight into the trade dynamics of the UAE. Figure 5 probably shows that the UAE consistently conducts business with its top trading partners. This consistency in trading partners may signify some dependability and mutual benefit in these economic ties. Figure 5 may represent the trade balance between the UAE and its main trading partners similar to Figure 4. With certain nations, a recurring trade surplus or deficit can have serious economic repercussions.



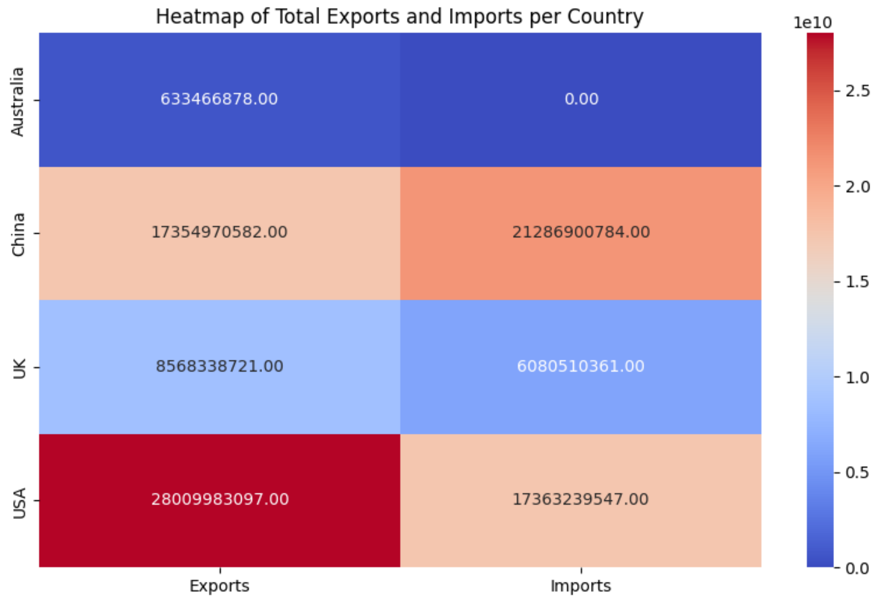

**(All units are in Thousands USD)*

Figure 5: Comparison of imports and exports from UAE with top trade partners

The statistics may show how heavily dependent the UAE is on certain nations for imports. Given how this dependence relates to supply chain resilience and diversification, economic policymakers may want to take it into account strategically. The export bars can be used to determine the main markets for UAE goods.

### 3.5 Heatmap Visualization for Trade Analysis

The trade relationships between the United Arab Emirates (UAE) and its main trading partners, including the United States (USA), China, the United Kingdom (UK), and Australia, are further examined and visualized in Figure 6, which is a heatmap representation. As seen in Figure 6, each heatmap cell represents a distinct trade relationship between the UAE and a specific nation. Each cell's color is graduated to show the size of the trade values. Higher values are denoted by darker, more intense colors, while lower values are denoted by lighter hues. This color scheme enables a quick evaluation of trade intensity.




*(*All units are in Thousands USD*)*

Figure 6: Heatmap of total exports and imports per country from UAE

The country that the UAE imports the most is indicated by the darkest cell in each row, and the country that the UAE exports the most is indicated by the darkest cell in each column. The information previously presented is visually reinforced by this comparison. Trade imbalances can be more easily identified by looking at the heatmap. Trade dynamics may alter over time. Researchers and decision-makers can spot changes in trade patterns by contrasting the heatmap with earlier data or other visualizations. For instance, if a cell in a recent heatmap that was previously lighter becomes darker, it denotes an increase in trade volume with that country.

### 3.6 Correlation Matrix of UAE Trade Values

The correlation matrix can be used to identify nations with comparable trade patterns. Predictions regarding the future trade values of various nations can be made using this data. The correlation matrix in Figure 7 shows the correlation between the trade values of various nations. The correlation coefficient determines the linear relationship between two factors. The perfect positive correlation is indicated by a correlation coefficient of 1, perfect negative correlation by a correlation coefficient of -1, and no correlation by a correlation coefficient of 0. Several significant correlations between the trade values of various countries have been discovered through analysis of the correlation matrix.

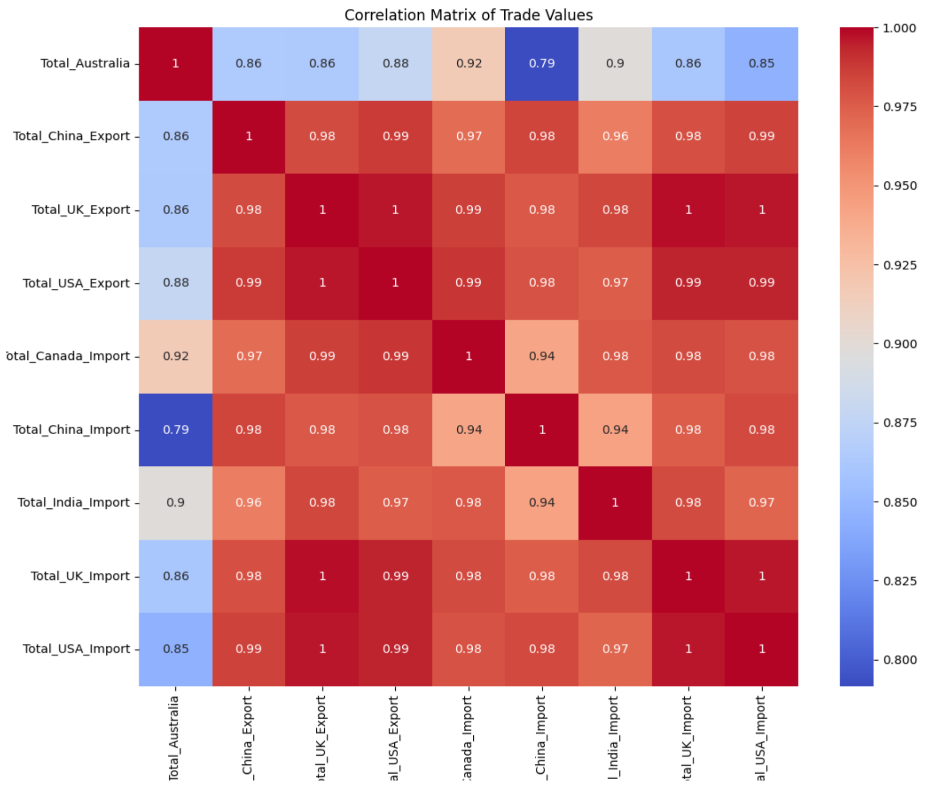



Figure 7: Correlation matrix of trade values

### 3.7 Trade Trend of UAE with Australia

Figure 8 shows the export values of products from the United Arab Emirates (UAE) to Australia. It is the comparison of the products that are top traded in 2021. The top 10 products by export value in 2021 are shown in Table 6 below:

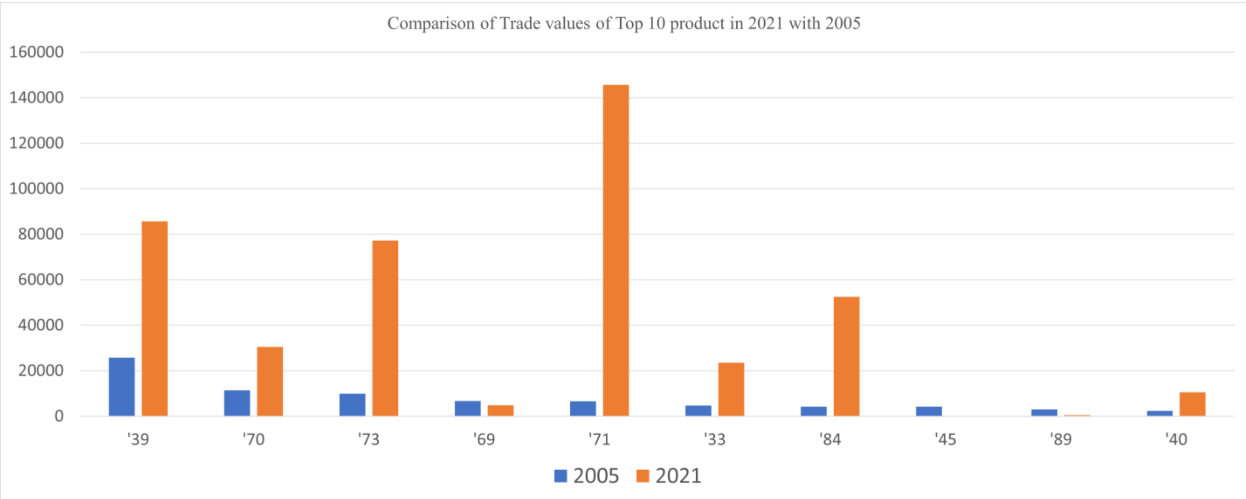
Table 6: Comparison of top products in 2021 with their trade values in 2005

| Product Code | 2005 | 2021 |
|---|---|---|
| '74 | 189 | 337507 |
| '71 | 6515 | 145651 |
| '39 | 25783 | 85667 |
| '73 | 9950 | 77243 |
| '85 | 936 | 66356 |
| '84 | 4272 | 52502 |
| '87 | 1280 | 36318 |
| '72 | 278 | 32664 |
| '70 | 11373 | 30515 |
| '33 | 4703 | 23513 |

*(*All units are in Thousands USD)*

The figure shows that the export values of the UAE to Australia have been increasing over the past few years. This is likely due to the strong economic growth in both countries. The UAE is a major oil exporter, and Australia is a major importer of oil. The UAE is also a major exporter of aluminum, plastics, and other manufactured goods, which are also in high demand in Australia. The fluctuations in the export values of the UAE to Australia can be due to several factors, such as changes in the global economy, changes in the political climate, and changes in the demand for specific products. For example, the decline in the export value of mineral fuels in 2020 can be attributed to the COVID-19 pandemic, which caused a global economic slowdown.

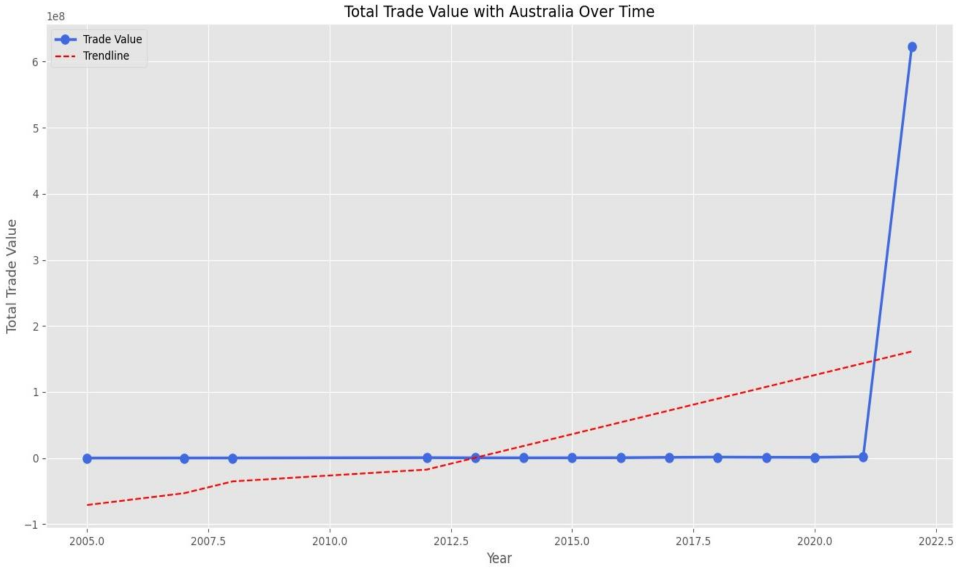
Figure 8 shows that the export values of the UAE to Australia are strong and are likely to continue to grow in the future. This is good news for both countries, as it will help to boost their economies and create jobs. Figure 8 shows the top 21 products traded with Australia. It shows the comparison of the trade values of these products in 2005. The huge spikes can be seen in the figure that shows the growing trend of trade between Australia and UAE. On the X-axis, HS code of the product is shown and on the Y-axis, the value of the trade is shown.




*(All units are in Thousands USD)*

Figure 8: Top 10 Products traded between UAE and Australia in 2021 comparing with 2005

In Figure 9, a line graph of the trade value between the UAE and Australia is shown. The trend line is a line that best fits the data points. It can be used to predict the future value of the trade value. The trend line also shows that the rate of increase is slowing down. This is likely due to numerous factors, including the global economic slowdown and the decline in oil prices. Despite the slowdown, the trend line indicates that the trade value between the UAE and Australia will continue to increase in the future. This is because the two countries have strong economic relations and there is a growing demand for goods and services from them.

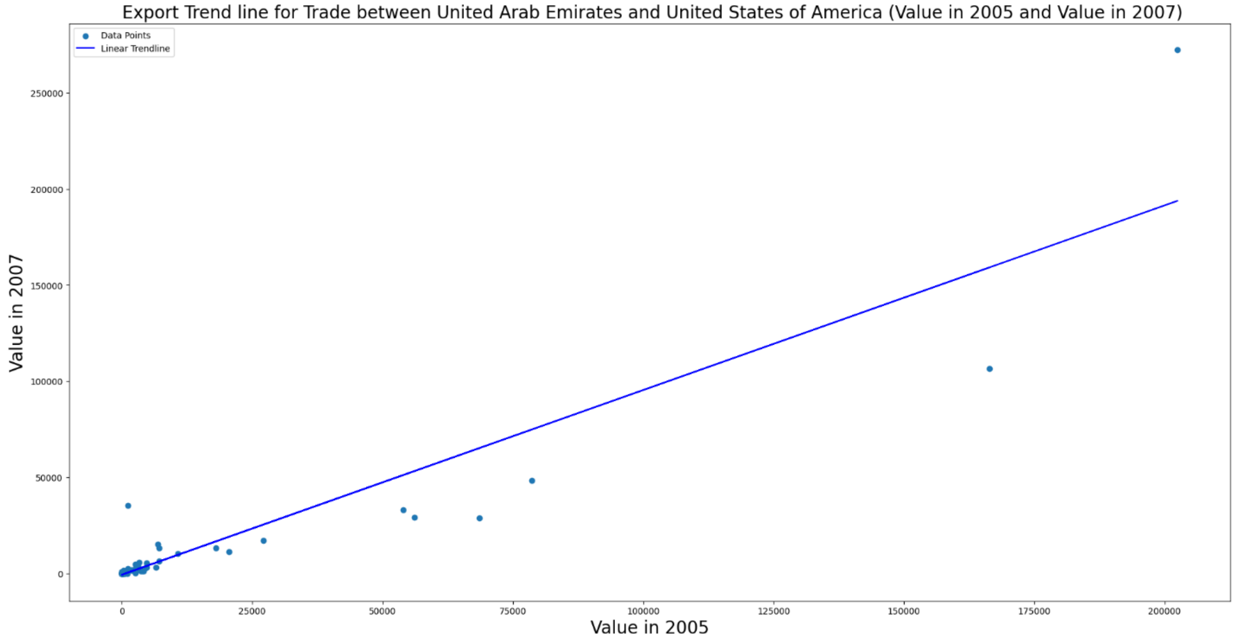



*(All units are in Thousands USD)*

Figure 9: Trade value of Australia with UAE

### 3.8 Trade Trend of UAE with USA

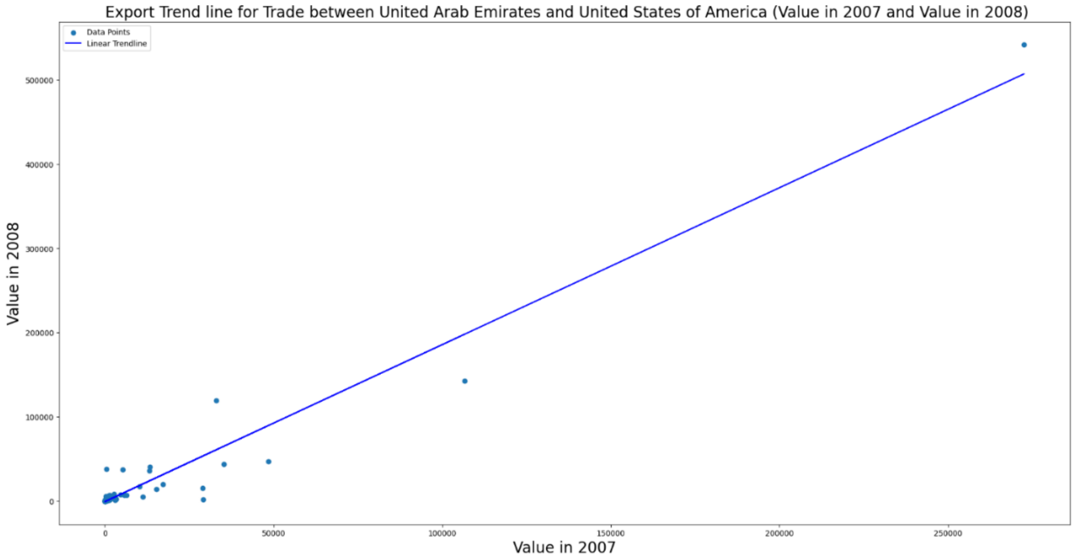
Figure 10 shows the export trend line from trade between the United Arab Emirates and the United States of America. The line represents the average value of the trade between the United Arab Emirates and the United States of America.




**(All units are in Thousands USD)*

Figure 10: Trade trend of UAE-USA between 2005 and 2007

The graph shows that the value of exports from the UAE to the USA has increased steadily over time. In 2005, the value of exports was around $25 billion. By 2007, the value of exports had increased to around $75 billion. The graph also shows that the value of exports from the UAE to the USA has been relatively stable since 2007. There have been some fluctuations in the value of exports from year to year, but the overall trend has been one of stability.

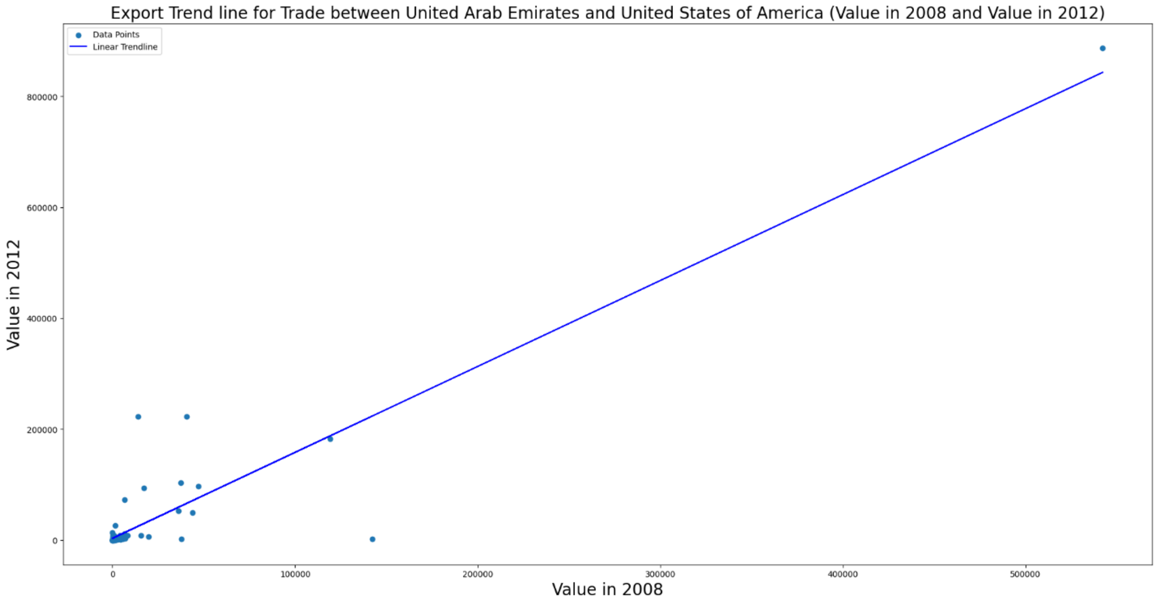



**(All units are in Thousands USD)*

Figure 11: Trade trend of UAE-USA between 2007 and 2008

The graph shown in Figure 11 is a scatter plot of the trade between the United Arab Emirates and the United States of America, with the value of exports from the UAE to the USA in 2008 on the y-axis and the value of exports from the UAE to the USA in 2007 on the x-axis. The graph also shows a linear trendline, which is a line that best fits the data points.

The trendline shows that there is a positive correlation between the value of exports from the UAE to the USA in 2007 and the value of exports from the UAE to the USA in 2008. This means that the higher the value of exports from the UAE to the USA in 2007, the higher the value of exports from the UAE to the USA in 2008 was. The trendline also shows that the value of exports from the UAE to the USA increased from 2007 to 2008. This is because the trendline is above the line y = x. The R-squared value of the trendline is 0.98. This means that the trendline explains 98% of the variation in the data. This is a very strong correlation, which suggests that the trendline is a good fit for the data. The graph shown in Figure 11 depicts that there is a strong positive correlation between the value of exports from the UAE to the USA in 2007 and the value of exports from the UAE to the USA in 2008. The graph also shows that the value of exports from the UAE to the USA increased from 2007 to 2008.

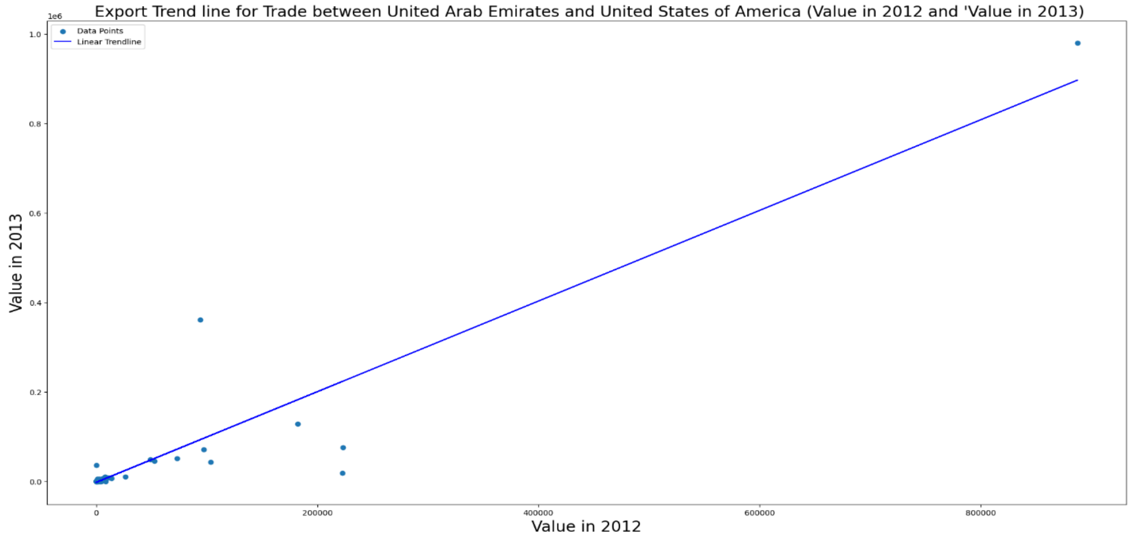



*(All units are in Thousands USD)*

Figure 12: Trade trend of UAE-USA between 2008 and 2012

The graph shown in Figure 12 is a scatter plot of the trade between the United Arab Emirates and the United States of America, with the value of exports from the UAE to the USA in 2012 on the y-axis and the value of exports from the UAE to the USA in 2008 on the x-axis. The graph also shows a linear trendline, which is a line that best fits the data points.

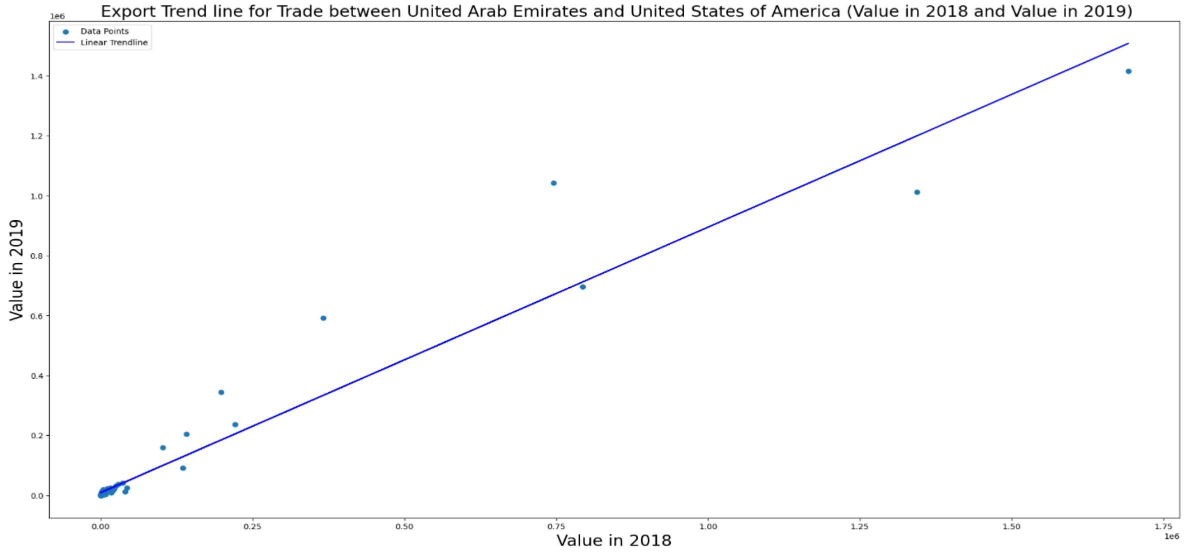
The trendline shows that there is a positive correlation between the value of exports from the UAE to the USA in 2008 and the value of exports from the UAE to the USA in 2012. This means that the higher the value of exports from the UAE to the USA in 2008, the higher the value of exports from the UAE to the USA in 2012 was.




*(All units are in Thousands USD)*

Figure 13: Trade trend of UAE-USA between 2012 and 2013

Figure 13 consists of a graph that shows a scatter plot of the export trend line for trade between the United Arab Emirates and the United States of America in 2012 and 2013. The x-axis shows the value of exports in 2012 and the y-axis shows the value of exports in 2013. The trendline shows the average value of exports from the UAE to the USA between 2012 and 2013.



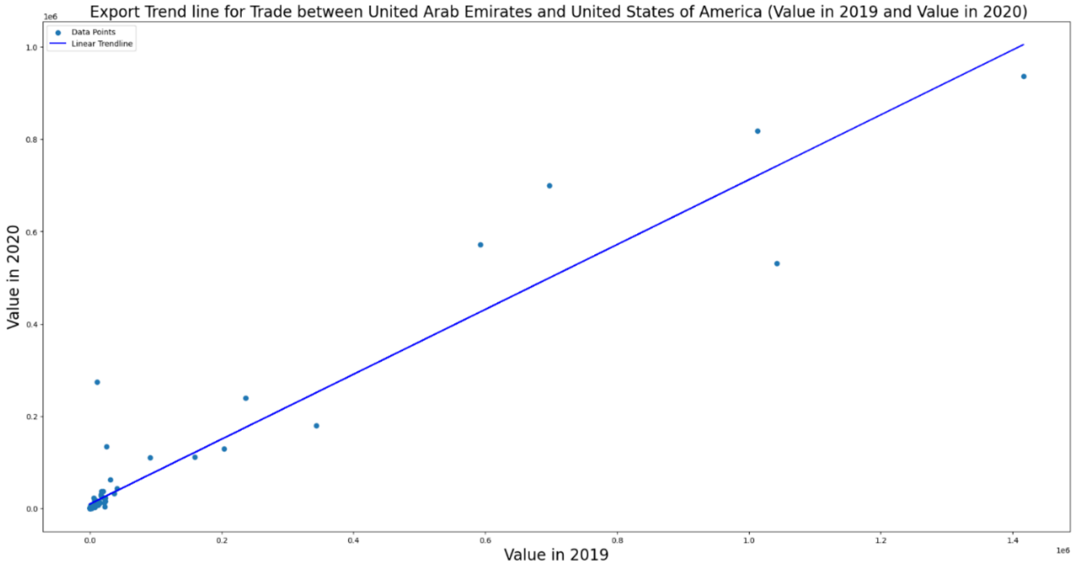

*(All units are in Thousands USD)*

Figure 14: Trade trend of UAE-USA between 2018 and 2019

Figure 14 shows the graph of exports from the UAE to the USA that decreased slightly from $75 billion in 2018 to $73 billion in 2019. This represents a decrease of approximately 3%.

The decline in exports from the UAE to the USA in 2019 is likely due to several factors, including:

- The global economic slowdown.
- The decline in oil prices.
- The trade war between the US and China.



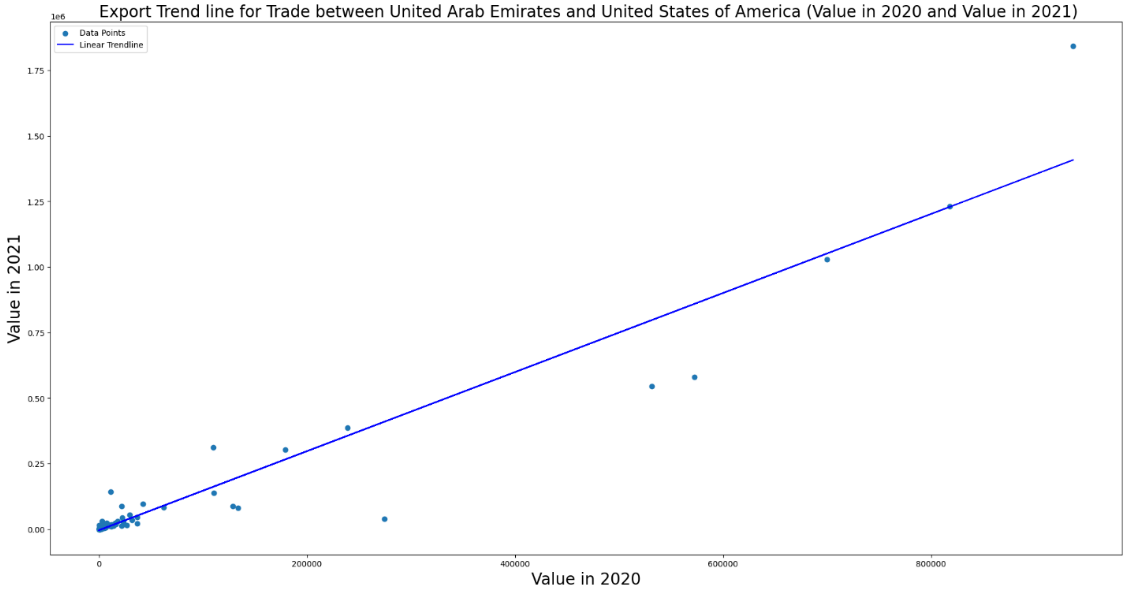

**(All units are in Thousands USD)*

Figure 15: Trade trend of UAE-USA between 2019 and 2020

The trading trend shown in Figure 15 between the UAE and the USA from 2019 to 2020 was also slightly negative similar to the trend between 2018 and 2019. The value of exports from the UAE to the USA decreased slightly by approximately 3%.

The decline in exports from the UAE to the USA in 2020 is likely due to several factors, including:

- The global economic recession caused by the COVID-19 pandemic.
- The decline in oil prices.
- The trade war between the US and China.




*(All units are in Thousands USD)*

Figure 16: Trade trend of UAE-USA between 2020 and 2021

The trade between the USA and the UAE has been increasing. The United States exported $14.9 billion to the UAE and imported $5.6 billion from the UAE in 2021, for a total bilateral trade value of $20.5 billion. This is an increase from the previous year of 16%. Transportation equipment, machinery and mechanical appliances, and electrical machinery and equipment are the major US exports to the UAE. Petroleum goods, aluminum, and precious stones are the main UAE exports to the USA.

The UAE is the United States' greatest trading partner in the Middle East and its 19th-largest trading partner overall. After China, the US is the UAE's second-largest trading partner worldwide. The trade trend shown in Figure 16 between the UAE and the USA is expected to continue to grow in the coming years, as both countries are committed to strengthening their economic relations. The UAE is also investing heavily in expanding its economy, which is creating new opportunities for US businesses.

### 3.9 Import Trade of UAE from USA

Figure 17 illustrates the import trade dynamics between the United Arab Emirates (UAE) and the United States of America (USA) spanning from 2005 to 2021. It portrays a clear picture of how the value of imports has evolved during this period in the Figure 17, the x-axis denotes the years, and the y-axis denotes the import values in billions of US dollars.

The trendline in the graph shows a general upward trajectory, signaling that the value of imports from the USA to the UAE has predominantly been on the rise, although with some random variations. Particularly, the total value of imports from the USA exhibited significant growth, surging from $10.3 billion in 2005 to a significant $20.1 billion by 2021.

This gradual rise in imports can be attributed to several key factors. For example, the USA and the UAE share a robust economic partnership. The UAE, endowed with substantial oil and gas resources, complements the USA's technological and manufacturing prowess. This economic cooperation gives strength to trade between the two nations.

The UAE is actively pursuing economic diversification as part of its strategy to reduce its dependency on oil and gas exports. One facet of this diversification strategy involves increasing the importation of goods and services from other countries, including the USA.

Another aspect is that the UAE's strategic geographical location as a gateway to both the Middle East and Africa enhances its attractiveness as a prime destination for imports from the USA. This strategic position facilitates trade flows and strengthens the UAE's role as a key trading hub in the region.

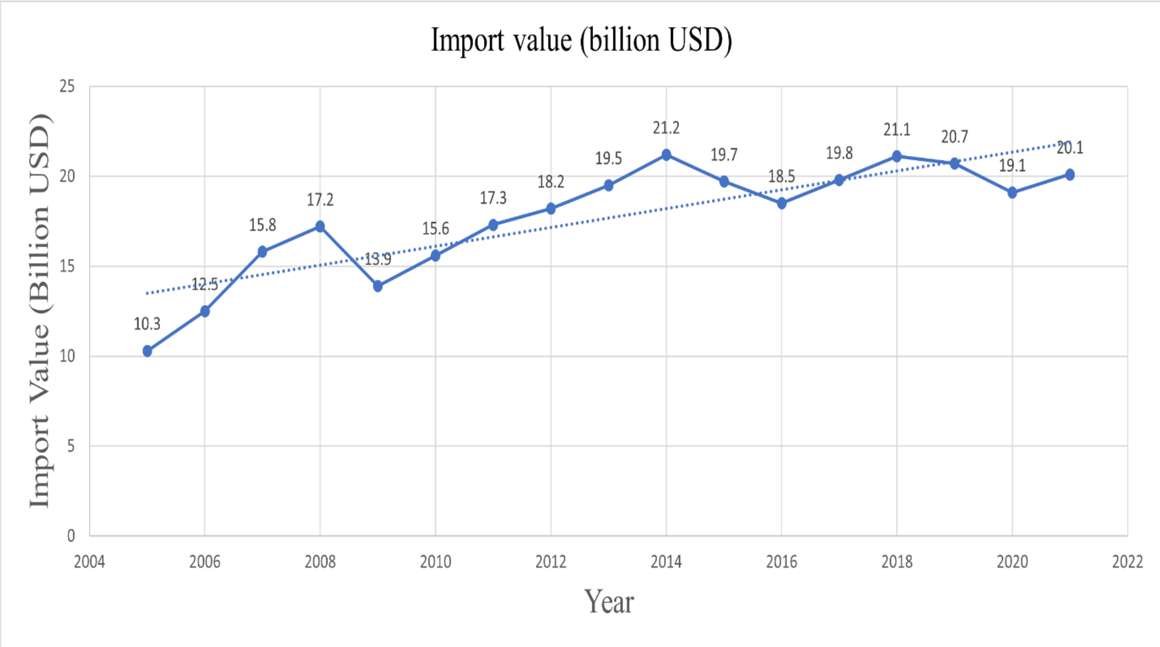
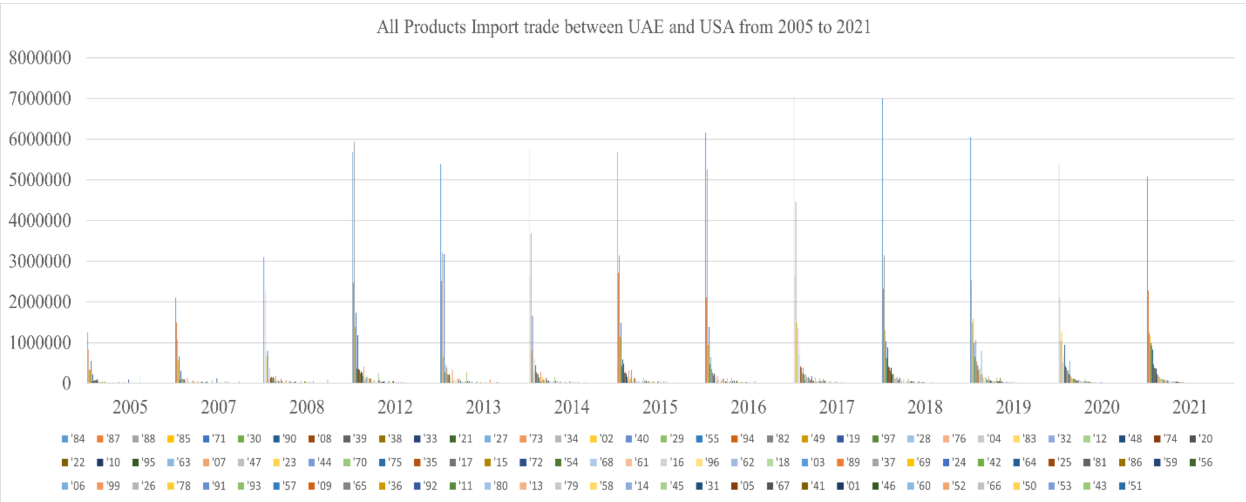



Figure 17: Import trade between UAE-USA from 2005 to 2021

UAE and USA have strong relations with each other and their trade is increasing day by day with a positive trend line as shown in Figure 17. Figure 18 shows all products traded between UAE and USA from 2005 to 2021. This bar plot shows the trade value of every HS product between these two countries.




*(*All units are in Thousands USD*)*

Figure 18: All HS product's import trade from 2005 to 2021

The import trade pattern between UAE and USA changed over time. The top 10 products in import trade between UAE and USA are shown in Table 7. The Following HS Products remained the top products in the year 2021.

- '84: Nuclear Reactors, Boilers, Machinery, and Mechanical Appliances
- '87: Vehicles other than Railway or Tramway Rolling Stock, and Parts and Accessories thereof.
- '88: Aircraft, Spacecraft, and Parts thereof.
- '85: Electrical Machinery and Equipment, and Parts thereof; Sound Recorders and Reproducers, and Parts and Accessories of such Articles.
- '71: Natural or Cultured Pearls, Precious or Semi-Precious Stones, Precious Metals, Metals Clad with Precious Metal, and Articles thereof; Imitation Jewelry; Coin.
- '30: Pharmaceutical Products.
- '90: Optical, Photographic, Cinematographic, Measuring, Checking, Precision, Medical or Surgical Instruments and Apparatus; Clocks and Watches; Musical Instruments; Parts and Accessories thereof.
- '08: Edible Fruit and Nuts; Peel of Citrus Fruit or Melons.
- '39: Plastics and Articles thereof.
- '38: Miscellaneous Chemical Products.

Table 7: Top 10 products imported from UAE in 2021 by USA

| Product Code | 2021 |
|---|---|
| '84 | 5080255 |
| '87 | 2281896 |
| '88 | 1247715 |
| '85 | 1179753 |
| '71 | 997520 |
| '30 | 933831 |
| '90 | 834848 |
| '08 | 472115 |
| '39 | 385738 |
| '38 | 373496 |

*(All units are in Thousands USD)*

### 3.10 LSTM Predictions

A Python script was developed to create a visual comparison between the predicted and actual values for the dataset. The code proceeds the following steps:

- To begin, a figure of size 15 x 15 inches is generated using fig = plt.figure(figsize=(15, 15)). This sets the dimensions for the visual representation.
- The figure is then divided into two subplots, creating a side-by-side arrangement for comparison. Subplot ax1 is defined as fig.add_subplot(221), and ax2 is defined as fig.add_subplot(222).

- In ax1, the script employs ax1.plot(ypred, 'r', label="Predictions") to plot the predicted values in red ('r') with the label "Predictions." This subplot is dedicated to visualizing the model's predictions.
- On the other hand, ax2 is dedicated to displaying the actual values. Using ax2.plot(ytrain, 'b', label="Actual"), the actual values are plotted in blue ('b') with the label "Actual."
- For both subplots, labels are set for the x-axis and y-axis, where ax1.set_xlabel("Time") and ax1.set_ylabel("Value") are used to label the predicted values, while ax2.set_xlabel("Time") and ax2.set_ylabel("Value") label the actual values. Additionally, titles are assigned to each subplot: "Predicted Values" for ax1 and "Actual Values" for ax2.
- The plt.show() function is then called to display the figure, presenting a visual comparison of predicted and actual values over time.

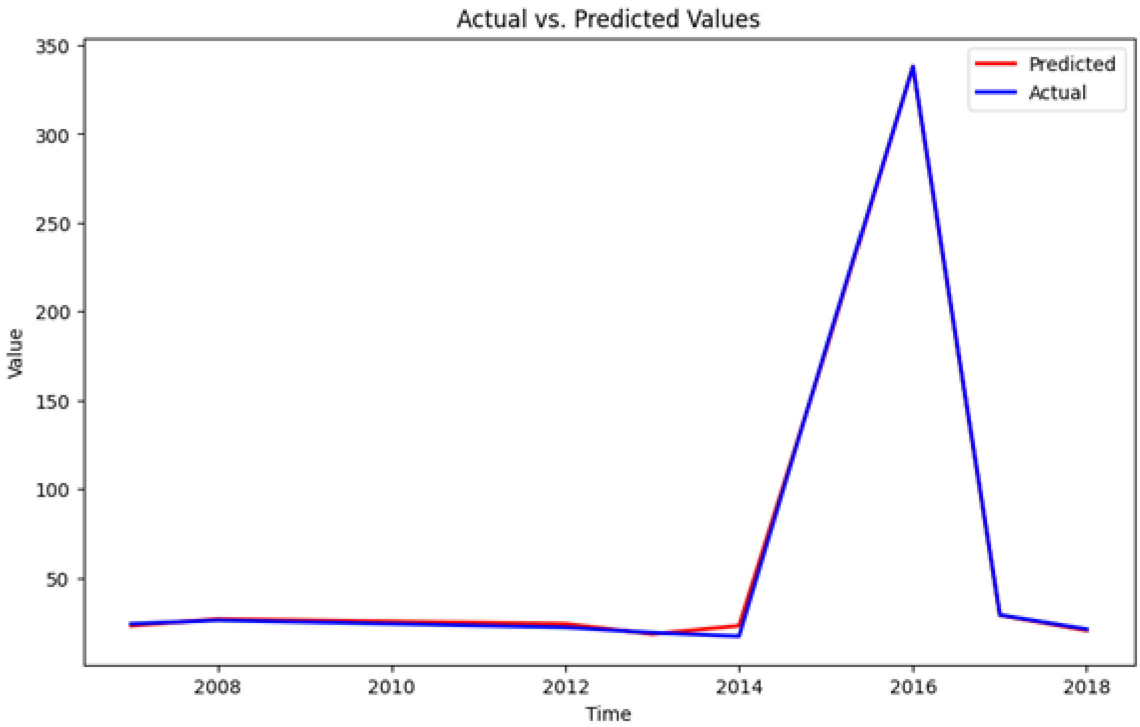
This script and code arrangement provide a clear visual representation, enabling an easy comparison between the model's predictions and the actual values in the dataset.

The implementation of this code played a pivotal role in visually assessing the model's performance against the training data, a critical step in the data analysis process. Below, we will present graphical representations, showcasing predictive curves alongside the corresponding actual ones for both imports and exports between the UAE and other countries, as well as the UAE's imports and exports on a global scale.

### *3.10.1 UAE Exports to Australia*

As shown in Figure 19, looking into the actual values, observed trend in the data is notably smooth, with export values remaining relatively consistent until 2015. In 2016, there was a discernible increase in exports, but the overall trend remained stable. This consistency in the dataset's trend provides an advantageous foundation for the LSTM model to comprehend and make accurate forecasts. Evaluating of the LSTM Model's forecast, the Mean Squared Error (MSE) for this model is impressively low at 0.0065, signifying a high level of reliability for forecasting. An MSE value below 1 is considered satisfactory, underscoring the model's dependability.

Evidently, the model exhibits an exceptional capacity to adeptly learn from the data and provide precise forecasts. Notably, this proficiency is demonstrated even with a relatively small dataset, affirming the model's effectiveness in grasping intricate patterns and making accurate predictions.

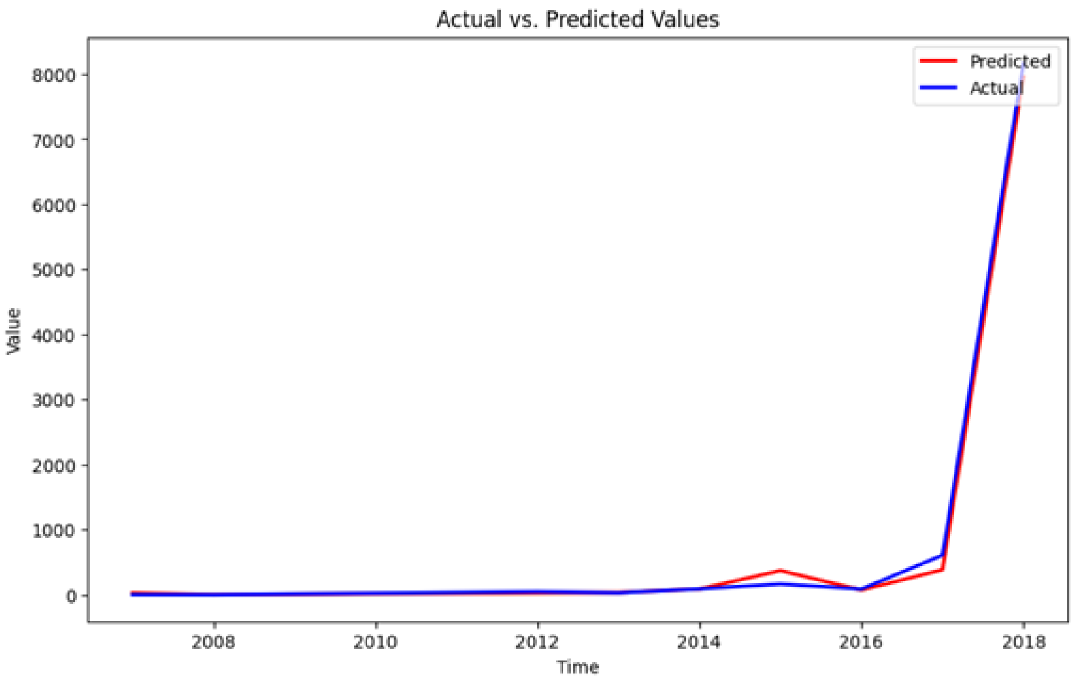



*(All units are in Thousands USD)*

Figure 19: UAE exports to Australia - predicted vs. actual values

*3.10.2 UAE Exports to China*

In this analysis, we will delve into the forecasting of exports from the UAE to China, spanning the years 2003 to 2022. It's noteworthy that the model architecture and hyperparameters remain consistent throughout, underscoring the efficacy of our finely tuned model in grasping intricate patterns from diverse trend datasets. Figure 20 shows the actual vs. predicted values depicting the real export trajectory to China.



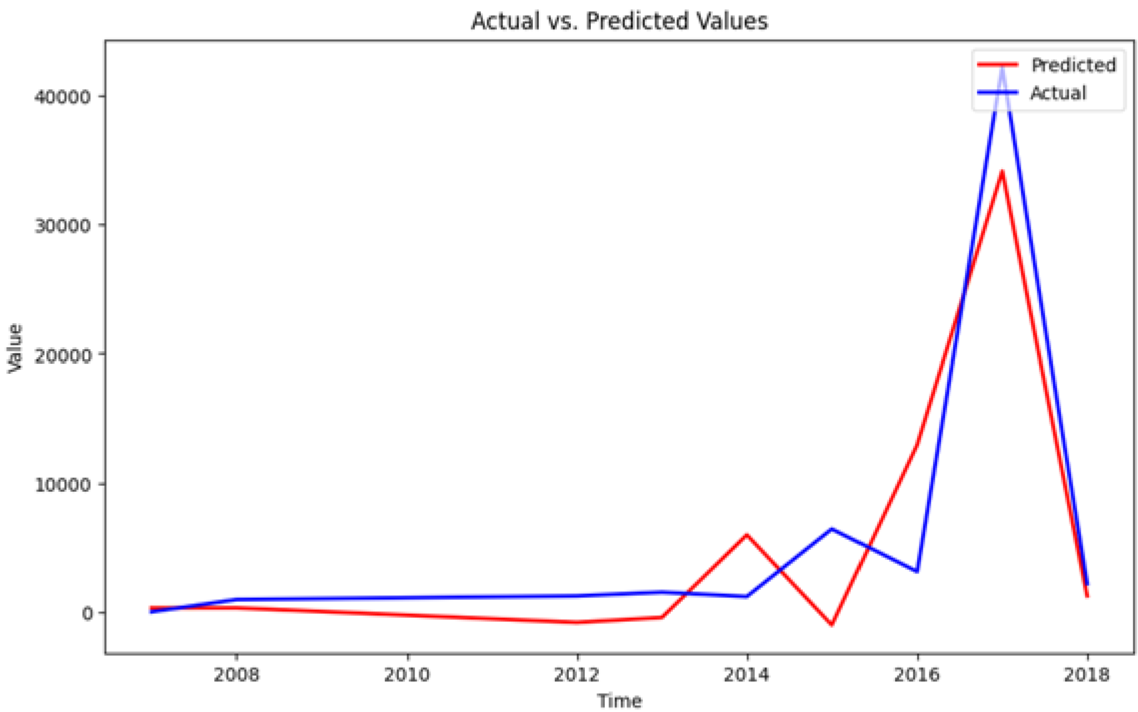

*(All units are in Thousands USD)

Figure 20: UAE exports to China - predicted vs. actual values

The model undergoes training on this dataset, achieving a commendable Mean Squared Error (MSE) loss value of 0.0021, indicative of its precise performance, bearing testament to our model's robust performance, resulting in accurate forecasting over a dataset characterized by varying trends in values.

*3.10.3 UAE Exports to UK*

In our effort to forecast product exports to the UK, our model has been diligently fine-tuned to provide accurate predictions while capturing the inherent complexities of the dataset.




*(All units are in Thousands USD)

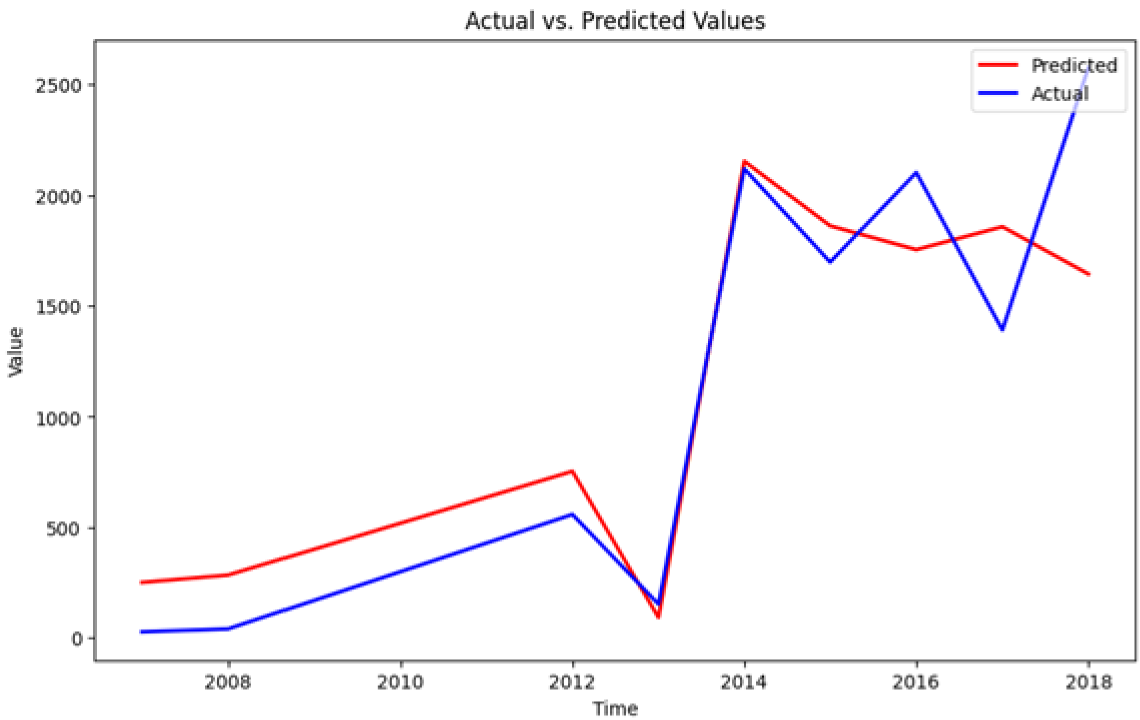
Figure 21: UAE exports to UK - predicted vs. actual values

As shown in Figure 21, the observed trend is characterized by significant variations with numerous peaks and valleys, necessitating a complex model to effectively capture these intricate features.

The Mean Squared Error (MSE) value is calculated at 0.3650, indicating that while the model maintains good accuracy, it faces greater challenges due to the more intricate trends in the data. Nevertheless, these results are deemed satisfactory for a general-purpose model.

*3.10.4 UAE Exports to USA*

Upon training, the model successfully achieves a Mean Squared Error (MSE) loss value of 0.4305. While this performance is commendable, it's noteworthy that achieving a near-zero loss value (around 0.00) would indicate even higher accuracy. However, given our model's fine-tuning to accommodate various datasets, it sometimes achieves exceptionally high accuracy and at other times reaches a level of performance just shy of perfect. It's important to maintain a balance as a reliable model should forecast values with a loss less than 1. Figure 22 presents a comparison between actual and predicted forecasts.



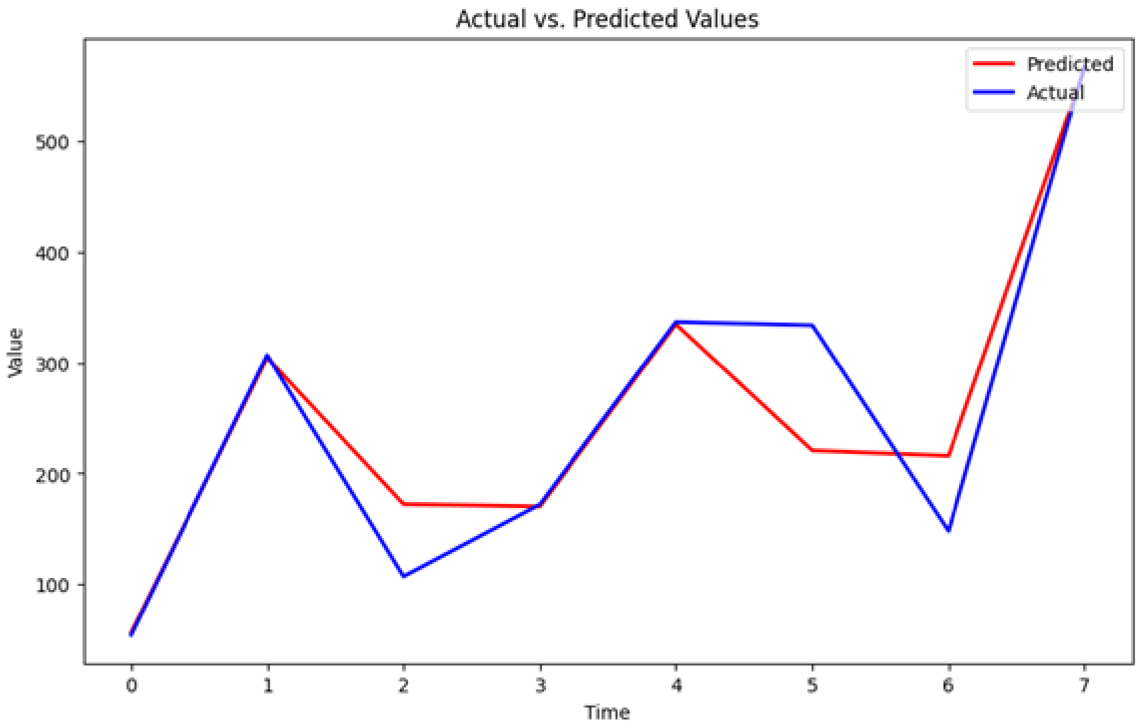

*(All units are in Thousands USD)

Figure 22: UAE exports to USA - predicted vs. actual values

*3.10.5 UAE Exports to Canada*

In the case of exports to Canada, we encountered a substantial number of null entries in most product categories. Considering the reduced dataset size, we adjusted the folds split to 5.

Notably, the export trend to Canada exhibits a unique complexity. While time series data often follows discernible trends, this dataset presents a less defined pattern, further complicated by a smaller number of data points. Despite these challenges, our LSTM model, which has been meticulously fine-tuned, manages to achieve a highly satisfactory Mean Squared Error (MSE) loss value of 0.1543. This exceptional result lends credibility to our model's forecasting capabilities. The forecasted result shown in Figure 23.

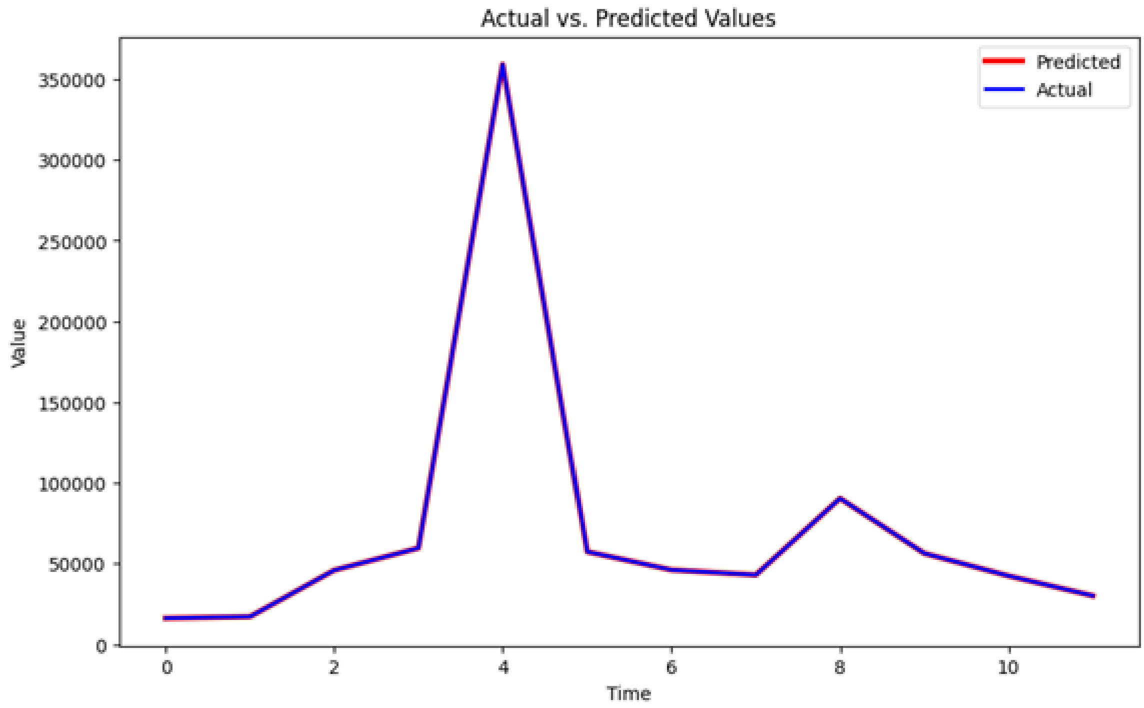



*(All units are in Thousands USD)

Figure 23: UAE exports to Canada - predicted vs. actual values

*3.10.6 UAE Exports to the World*

Below in Figure 24, the key difference to notice is that the trend in the data is quite clear and straightforward, but the values are exceptionally high, around 3,500,000. The model's loss, which is a measure of accuracy, is approximately 1. This higher loss is primarily because of the challenge posed by dealing with these high, unstandardized values, resulting in a less typical learning pattern.



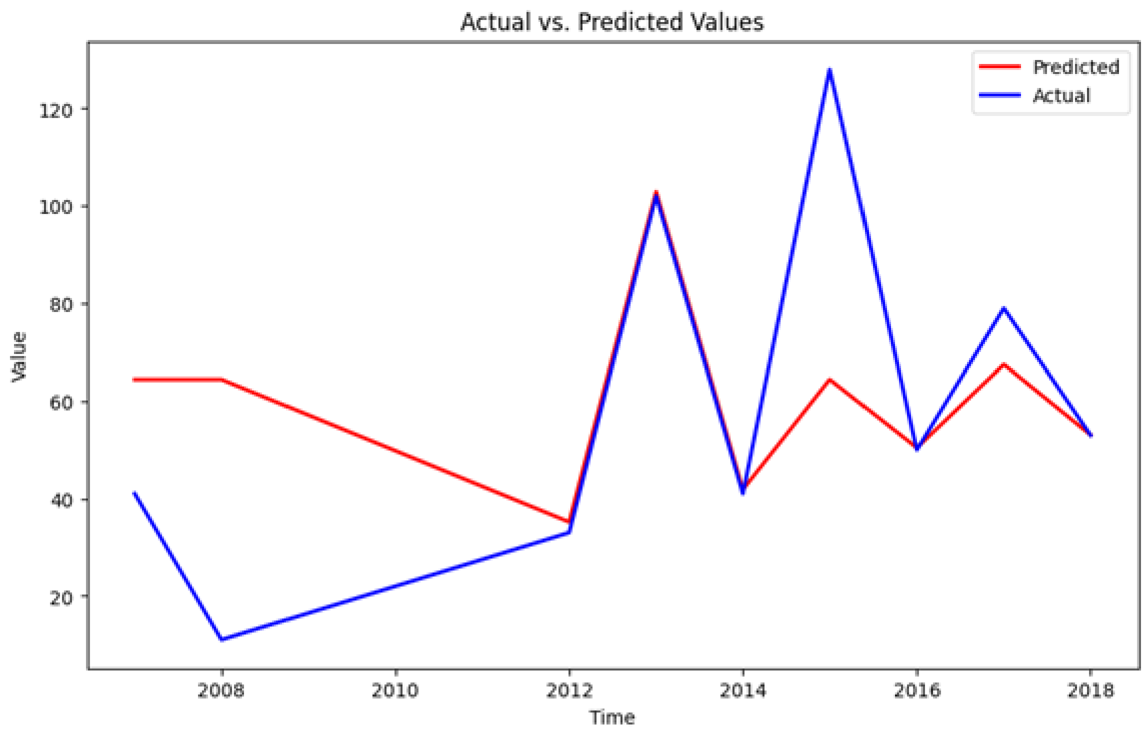

*(All units are in Thousands USD)

Figure 24: UAE exports to the world - predicted vs. actual values

While the model effectively captures the general trend, it does struggle with these high values. For instance, the highest predicted value is 85,000, while the actual values can reach up to 3,500,000. Even though this presents a significant difference, our well-tuned model still performs satisfactorily. This underscores the model's robustness and ability to handle a variety of scenarios. Additionally, we conducted experiments by making slight adjustments to the model's settings, including increasing the training epochs to 500, aiming to enhance its capability to learn complex patterns.

*3.10.7 Canada Imports to UAE*

The import dataset presents a highly intricate trend as seen in Figure 25. Notably, there are recurring cycles of rises and falls in imports, with a significant peak observed in 2020, likely attributed to the impact of COVID-19. It's important to emphasize that our model excels at capturing the overall trend in the dataset but may struggle to identify and adapt to unusual or anomalous trends. The loss resulting from model training is calculated at 0.2882. Below, we present the actual and predicted forecasts.



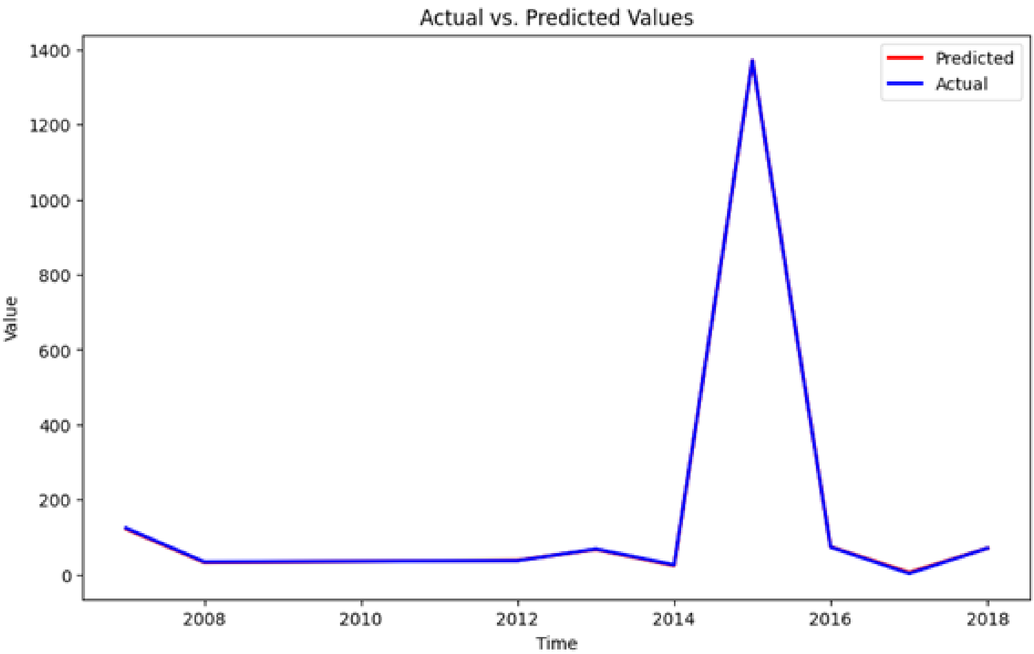

*(All units are in Thousands USD)

Figure 25: Canada imports to the UAE - predicted vs. actual values

As expected, our model effectively learns and replicates the overall trend. However, when faced with anomalies or unusual trends in the dataset, it may falter, resulting in inaccuracies in its forecasts. Nonetheless, the model consistently provides a highly accurate forecast of the general trend, maintaining a minimal loss and faithfully tracking the overall import trend.

*3.10.8 China Imports to the UAE*

The model achieved a notably lower loss, approximately 0.0094. This suggests that the model accurately captures the features and patterns within the dataset, and there are no anomalies or unusual behaviors in the trend. This straightforward trend makes it easier for the model to learn and make reliable forecasts. The actual and predicted forecasts are presented Figure 26.




**(All units are in Thousands USD)*

Figure 26: China imports to the UAE - predicted vs. actual values

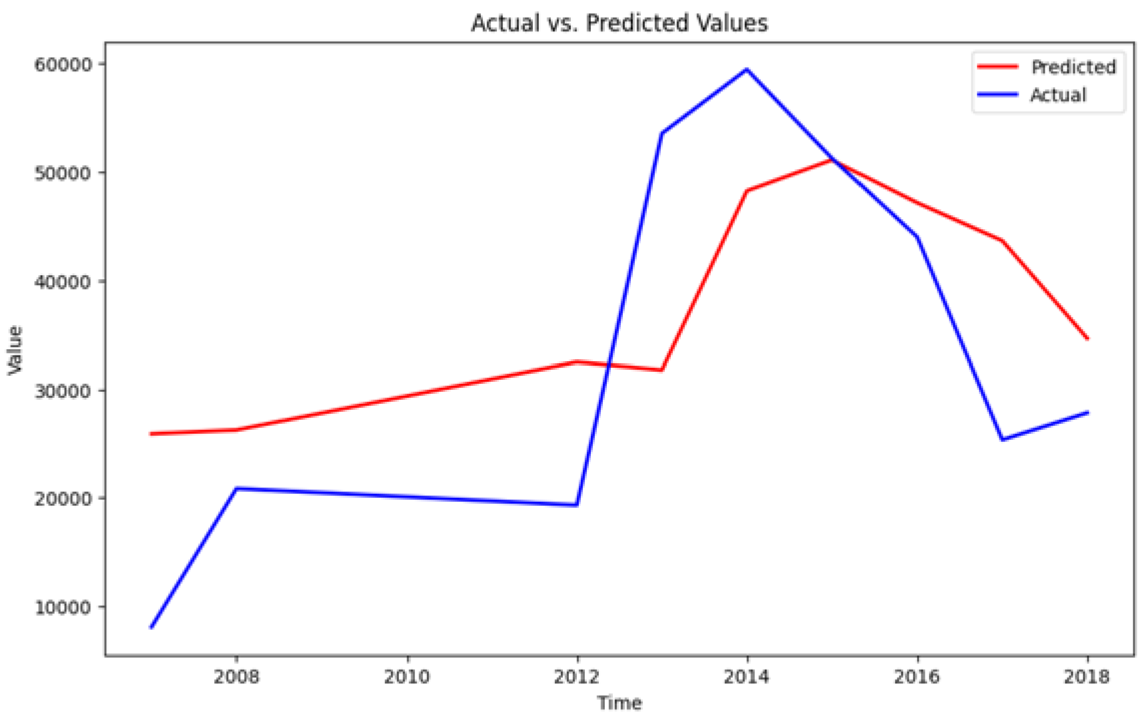
As shown in the Figure 26, the model has successfully learned even subtle trends within the dataset, providing highly accurate forecasts. This reliability is attributed to the absence of anomalies in the trend data. The primary difference observed is that the peak values in the actual dataset reach 1,400, while the model's predictions peak at 1,200. This variation, although minor, is satisfactory and does not indicate any major deviations or incorrect trends, further highlighting the effectiveness of our model.

*3.10.9 India Imports to the UAE*

Analyzing the import trend for India's total imports reveals a highly intricate pattern, presenting a challenge for the model in capturing these complex features.

The observed trend is characterized by abrupt rises and falls, lacking the smoothness of some other datasets. Despite this complexity, our model achieves a very satisfactory loss, approximately 0.7625. This value, falling between the ranges of very low and above 1, indicates that the model performs effectively in grasping the dataset's features without either underfitting or overfitting.

In Figure 27 above, it's evident that the model excels at learning these intricate features with impressive performance. The overall trend of rises and falls is accurately mirrored by the model. The primary distinction lies in the peak values, where the actual dataset reaches 60,000, while the model's forecast peaks at 47,500. Additionally, the model may not accurately predict declines. However, when considering the entire forecast, it remains highly satisfactory and reliable in capturing the complex import trend.



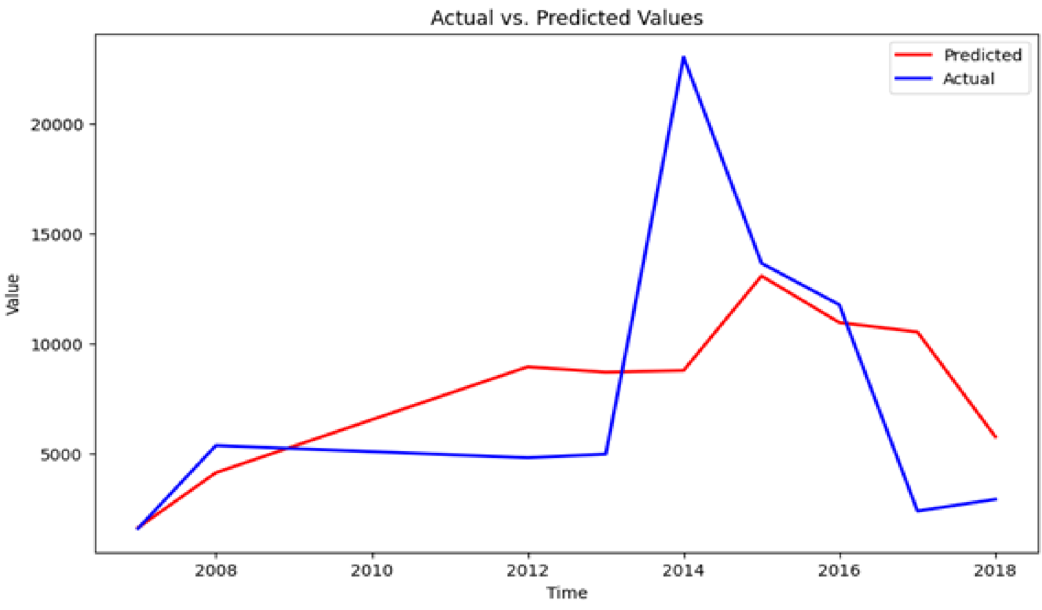

**(All units are in Thousands USD)*

Figure 27: India imports to the UAE - predicted vs. actual values

*3.10.10 UK Imports to the UAE*

As shown in Figure 28, for the evaluation of imports from the UK, this dataset lacks complex patterns or trends that would pose a significant challenge for the model's learning and forecasting capabilities. However, it's noteworthy that the model registers a somewhat higher loss, measuring 0.8129. This suggests that certain patterns or anomalies may be present in the data that are unusual for the model. Given that this is a highly tuned model, it is expected to capture the overall trend with a high degree of accuracy, and small anomalies in the forecast are acceptable.

As previously discussed, the model effectively captures the general trend. However, since there is a consistent rise in the trend, the model may struggle to learn these complex features. Nevertheless, the overall trend of the forecast remains accurate, indicating when imports are expected to increase or decrease. It's important to recognize that LSTM models excel at learning from time series data, and our dataset, with around 10-20 entries, does present limitations in terms of learning. If we had a larger dataset, regardless of its complexity or unusual trends, the model would provide very accurate results. However, even with limited data points and a single model trained for all imports and exports, the results remain highly satisfactory.

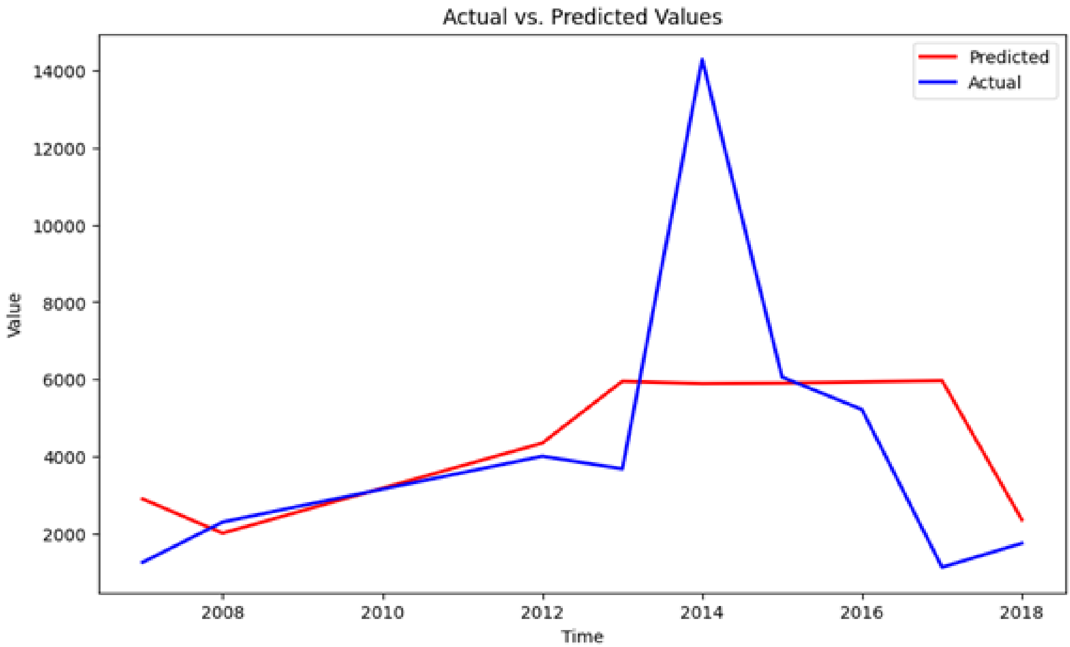



**(All units are in Thousands USD)*

Figure 28: UK imports to the  UAE - predicted vs. actual values

*3.10.11 USA Imports to the UAE*

In the evaluation of imports in the USA, the trend for the USA reveals a fairly steady pattern until 2014 when there was a notable increase in imports, followed by a subsequent decrease. Such a typical behavior can sometimes challenge the model's learning capacity unless it's finely tuned. Fortunately, in our case, we have meticulously fine-tuned our model to effectively learn complex features and deliver strong performance. The loss achieved by the model stands at 0.8117, which is a commendable value, as it falls below 1. The predicted and actual forecasts are presented in Figure 29.



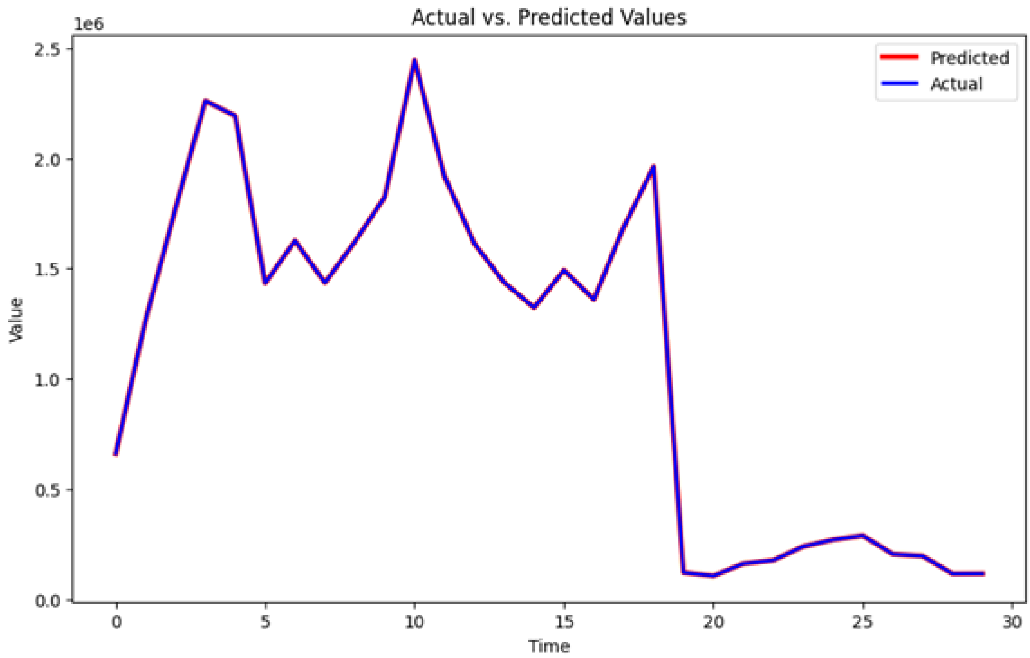

*(All units are in Thousands USD)*

Figure 29: USA imports to the UAE – predicted vs. actual values

It's evident that the model encounters difficulties when there is an unusual increase in imports. Nevertheless, it manages to capture this trend with good performance overall. Additionally, when dealing with a dataset of limited size, a single abnormal rise can pose challenges for the model's learning process. However, our model consistently demonstrates strong performance, effectively proving its reliability and effectiveness across various imports and exports datasets.

*3.10.12 The World's Imports to the UAE*

The import data was also analyzed for worldwide imports. The actual data shows a complex pattern, with yearly variations and exceptionally high values, making it a challenging dataset for the model to learn from. This complexity results in a loss value of 1, indicating difficulties in prediction. Predicted values display a similar trend after optimization with the help of cross validation.  LSTM models excel when data has a strong and consistent trend, and the model's suboptimal performance is attributed to the dataset's irregular behavior without a clear trend. Despite these challenges and the dataset's anomalies, the model's overall performance remains satisfactory.




*(All units are in Thousands USD)

Figure 30: The world's imports to the UAE – predicted vs. actual values

## 3.11 GDP Calculation Based on Imports and Exports

Gross Domestic Product (GDP) is the total value of all goods and services produced in a country during a given period of time. It is one of the most important economic indicators, as it provides a measure of the size and growth of an economy.

One way to calculate GDP is to use the expenditure approach. This approach calculates GDP by adding up the following four components:

- Consumer spending.
- Business investment.
- Government spending.
- Net exports.

Net exports are the difference between a country's exports and imports. If a country exports more goods and services than it imports, it has a trade surplus. If a country imports more goods and services than it exports, it has a trade deficit.

The following formula shows how to calculate GDP using the expenditure approach:

$$GDP = C + I + G + (X - M) \qquad \text{Equation (4)}$$

where:

C is consumer spending

I is business investment

G is government spending

X is exports

M is imports

Net exports are an important component of GDP because they represent the contribution of foreign investment to the domestic economy. When a country exports goods and services, it is essentially selling its production capacity to other countries. This investment helps to create jobs and boost economic growth.

We calculate GDP with above mentioned formula in Equation No 4. We used python libraries to calculate the GDP.

`df['C']` is the column in the DataFrame that contains consumer spending.

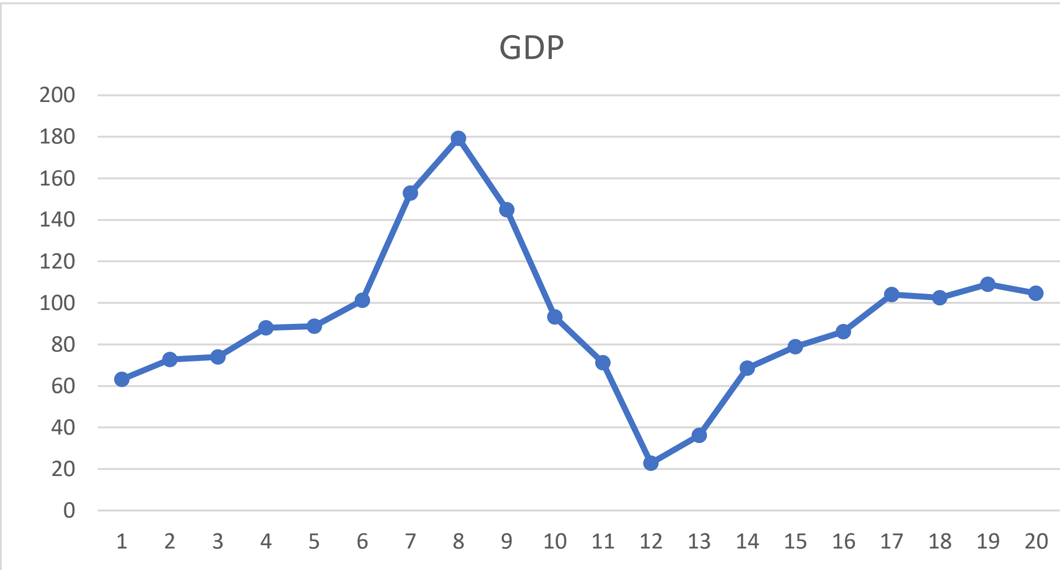
`df['I']` is the column in the DataFrame that contains business investment.

`df['G']` is the column in the DataFrame that contains government spending.

`df['X']` is the column in the DataFrame that contains exports.

`df['M']` is the column in the DataFrame that contains imports.

The used Python code implements the formula by adding up the corresponding columns in the DataFrame `df`. The result is a new column in the DataFrame `df` called GDP, which contains the `GDP` for each year. Figure 31 shows the GDP calculated by the above-mentioned equation from 2001 to 2020.




*(*All units are in Billion USD*)*

Figure 31: GDP from 2001 to 2020

We trained an LSTM model to predict the GDP on the basis of the formula discussed above.

The create_sequences() function creates sequences of data that can be used as input to the LSTM model. The function takes two arguments: the data and the number of time steps per sequence. The function iterates over the data, creating a sequence for each time step. The sequence for each time step is a list of the next time_steps values in the data. The function returns a NumPy array of sequences and a NumPy array of targets.

The LSTM model is built using the Sequential model from Keras. The model has two layers: an LSTM layer and a dense layer. The LSTM layer has 50 units and the dense layer has 1 unit. The LSTM layer is activated using the relu function. The dense layer is activated using the linear function. The model is compiled using the Adam optimizer and the mean squared error loss function.

The model is trained using the fit() method. The fit() method takes four arguments: the training data, the training targets, the number of epochs, and the batch size. The model is trained for 500 epochs with a batch size of 32. A validation split of 20% is used. The early stopping callback is used to stop training if the validation loss does not improve for 10 epochs. The reduced learning rate callback is used to reduce the learning rate if the validation loss does not improve for 5 epochs.

The provided code creates and trains an LSTM model to predict future values of a time series. The model can be used to predict future GDP, stock prices, or other time series data.

Figure 32 shows the training loss vs validation loss curve of LSTM model. The figure shows that the model converges after 260 epochs and here model early stops as we used early stopping mechanism in our python code. It early stops as the loss stops decreasing for ten consecutive iterations.

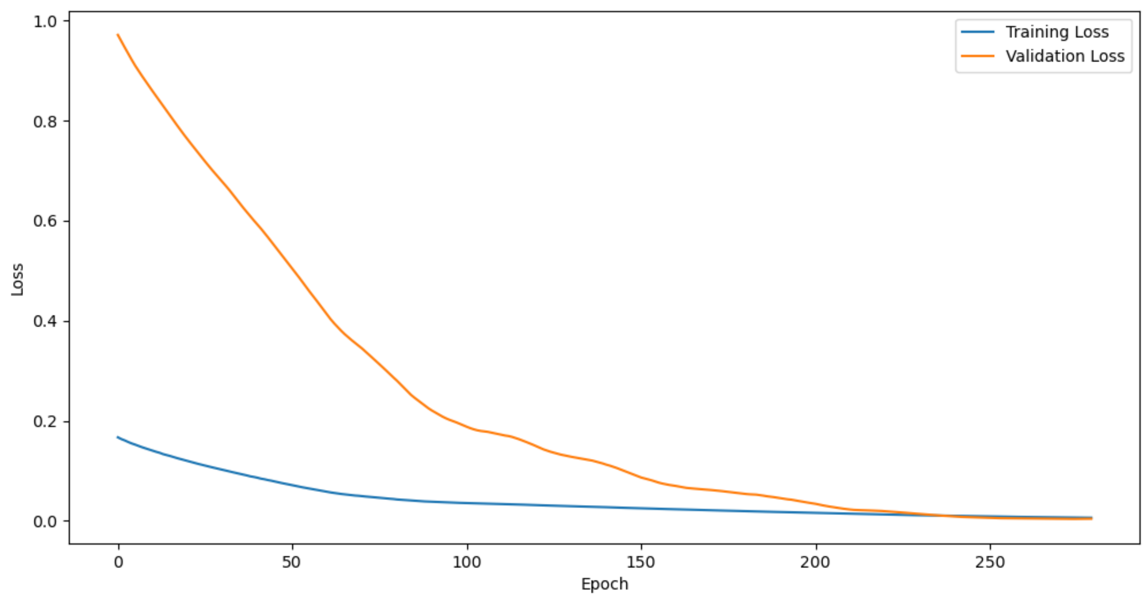



Figure 32: Training vs. validation loss curve of LSTM model

MSE loss is used in LSTM model for the evaluation of the model. Figure 32 shows the decreasing MSE loss on the independent data.

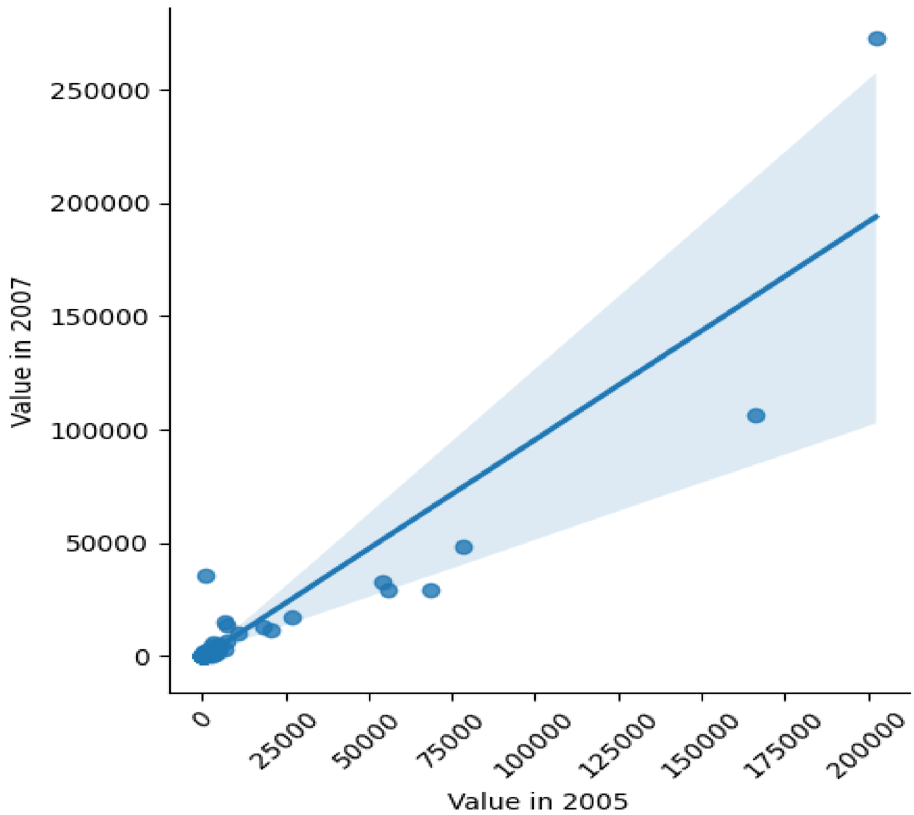
### 3.12 Model Performance Evaluation

We used Mean Squared Error (MSE), and Correlation matrices as evaluation matrices of our model. As seen previously in Figure 17, a comprehensive picture of the correlation coefficient between different trade values. If the correlation is high (close to 1), it indicates a strong linear relationship between the predictions and the actual values, suggesting that the model is doing a good job of capturing the linear trend in the data.

The training vs validation loss in Figure 32 shows the MSE loss values of training and validation. The mean squared error (MSE) loss function is used as a metric for LSTM model. It measures the average squared difference between the actual and predicted values. Lower MSE indicates a better model. Figure 32 clearly shows that the model after 200th iteration converges and the minimum difference between training MSE and validation MSE shows the significance of the model.

# Chapter 4: Discussions on Results

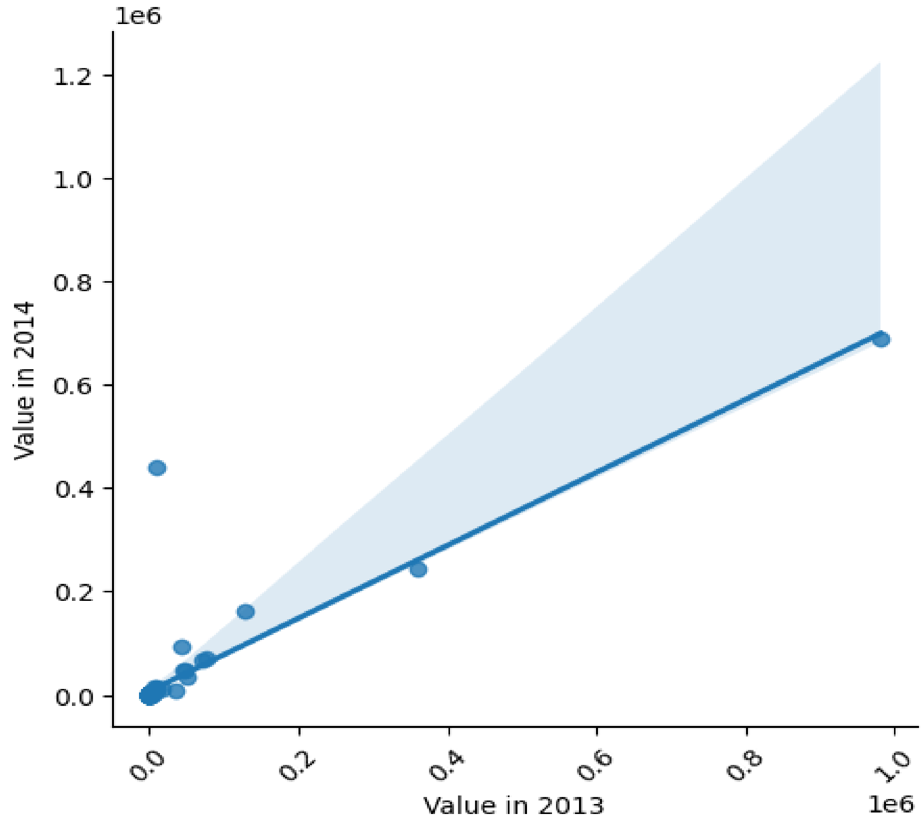
Results obtained from the LSTM model and visualization show that the trade of UAE is increasing rapidly despite global change and other factors. Figure 33 to 37 shows the trend analysis of each year with its previous year. It is UAE's overall trade.




*(All units are in Thousands USD)*

Figure 33: Trade trend between the year 2005 and 2007

The data points in Figure 33 in the graph are connected by a line, which indicates that the trend is linear. The line has a positive slope, which means that the value of trade is increasing. The line is not perfectly straight, which means that there is some variation in the data.

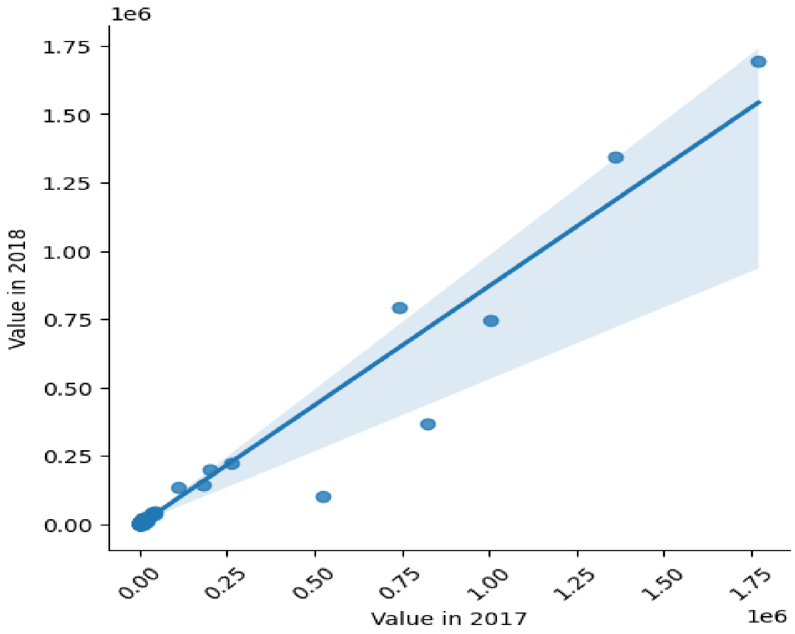



**(All units are in Thousands USD)*

Figure 34: Trade trend between the year 2013 and 2014

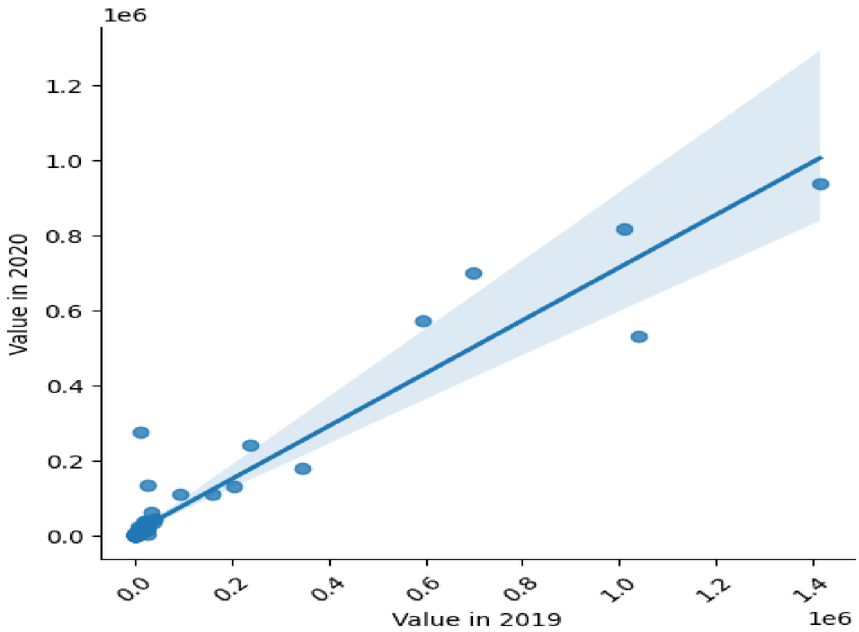
Although the rate of growth is not particularly rapid during this time, the trade trend observed in the United Arab Emirates (UAE) between 2013 and 2014 indicates a positive outcome as shown in Figure 34. This judgment is based on an analysis of trade data, which indicates that while trade activity is on the rise, it is not experiencing explosive or unexpected growth.

No significant increase in data points is seen between the years 2017 and 2018, as shown in Figure 35. Particularly when compared to the years before, this suggests that trade has no big increase during these years.




*(All units are in Thousands USD)*

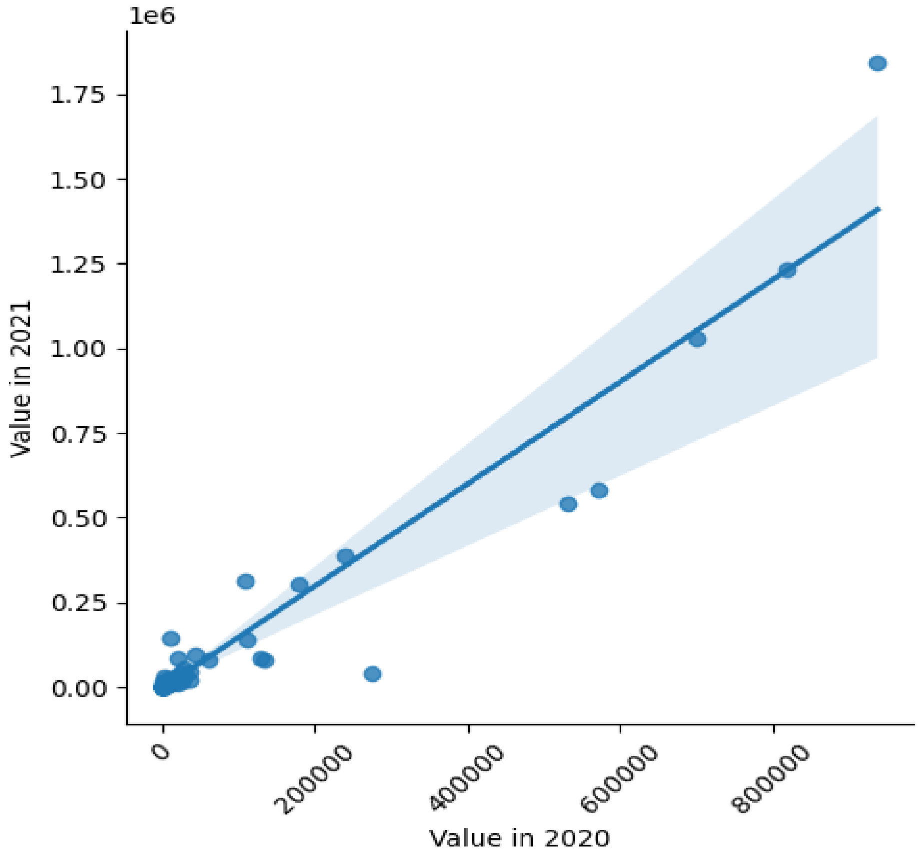
Figure 35: Trade trend between the year 2017 and 2018




*(All units are in Thousands USD)*

Figure 36: Trade trend between the year 2019 and 2020

As shown in Figure 36, the trade trend between 2019 and 2020 in the UAE resulted in a decline in both exports and imports as shown in Figure 36. Exports decreased by 11.7% from 314.5 billion in 2019 to 273.7 billion in 2020. Imports decreased by 10.3% from AED 280.2 billion in 2019 to AED 251.1 billion in 2020. This decline could be due to several factors, such as the COVID-19 pandemic, which caused a global economic slowdown and a decline in demand for goods and services. The decline in oil prices reduced the UAE's export earnings.



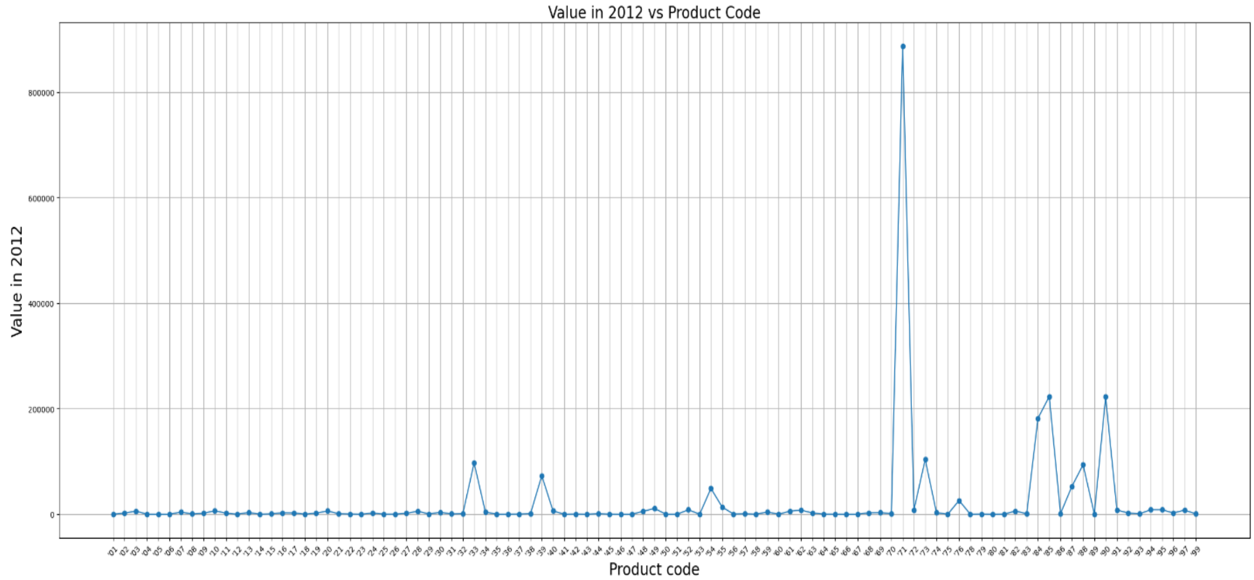

*(All units are in Thousands USD)*

Figure 37: Trade trend between the year 2020 and 2021

The trade pattern of UAE's exports and imports increased between 2020 and 2021, according to the trade pattern observed in Figure 37. From AED 273.7 billion in 2020 to AED 300.9 billion in 2021, exports increased by 10%. From AED 251.1 billion to AED 284.2 billion in 2021, imports rose by 13.4%. Several factors contributed to this increase: the COVID-19 pandemic-related slow global economic growth. The increase in oil prices, which increased export revenue for the UAE, led to the increase in oil prices. The UAE's efforts to reduce its dependence on oil exports and diversify its economy.

### 4.1 Yearly Product Wise Trade Analysis

In this section, we present the analysis of all the products traded in the UAE with different countries. The Harmonized System (HS) nomenclature of products is used. The HS is an international system of labeling goods for trade purposes. It is used by customs authorities worldwide to collect import and export duties and to monitor trade flows.

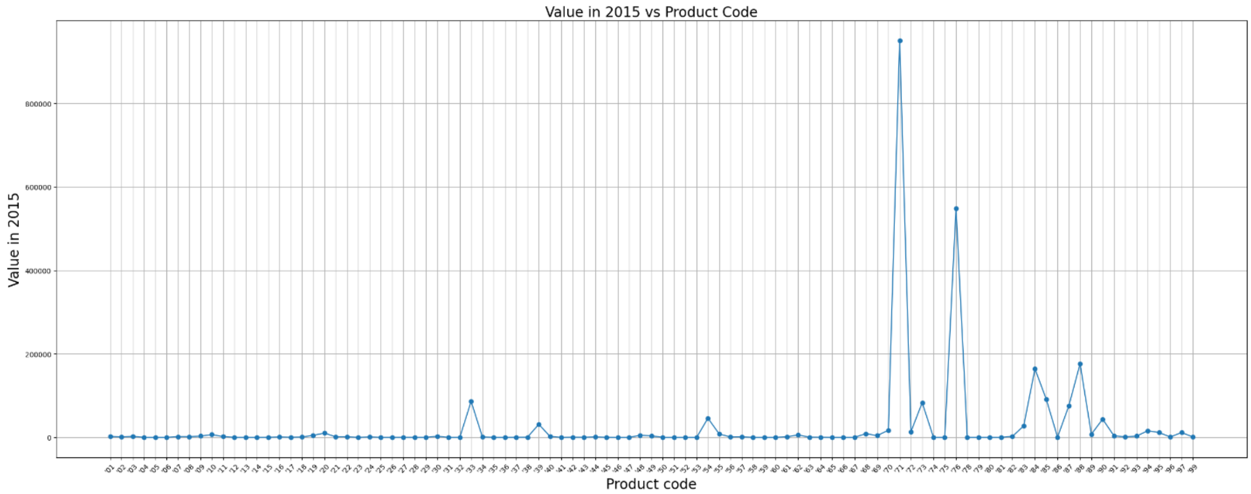



*(All units are in Thousands USD)*

Figure 38: Trade value of different products in UAE

UAE traded the HS-71 product as a top traded item with the USA as shown in Figure 38. HS-71 is a product that consists of natural or cultured pearls, precious or semi-precious stones, precious metals, metals clad. The second highest product traded in 2012 in UAE is HS-85 and HS-90 that is electrical machinery and equipment and parts thereof; sound recorders and reproducers, television and optical, photographic, cinematographic, measuring, checking, precision, medical or surgical.

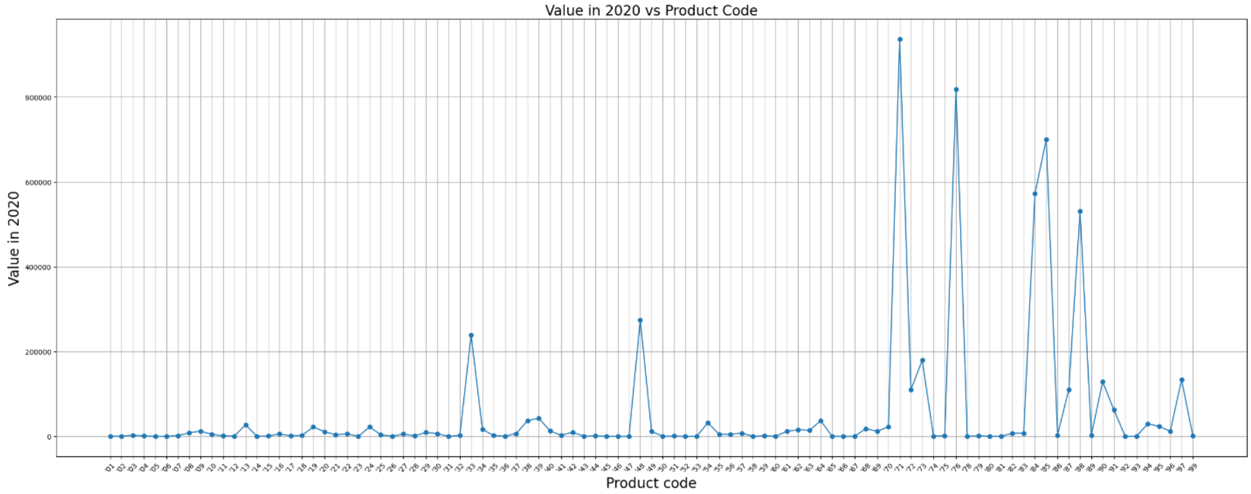
Comparing 2012 with 2015 the trade has changed in UAE as in 2015 there was a huge change in trade values with the USA as shown in Figure 39. UAE trade values in different products increased significantly. These products include HS-71, HS-76, HS-88, and HS-84, which are “Natural or cultured pearls, precious or semi-precious stones, precious metals, metals clad ...”, “Aluminium and articles thereof”, “Aircraft, spacecraft, and parts thereof”, and “Nuclear reactors, boilers, machinery, and mechanical appliances; parts thereof”, respectively.




*(All units are in Thousands USD)*

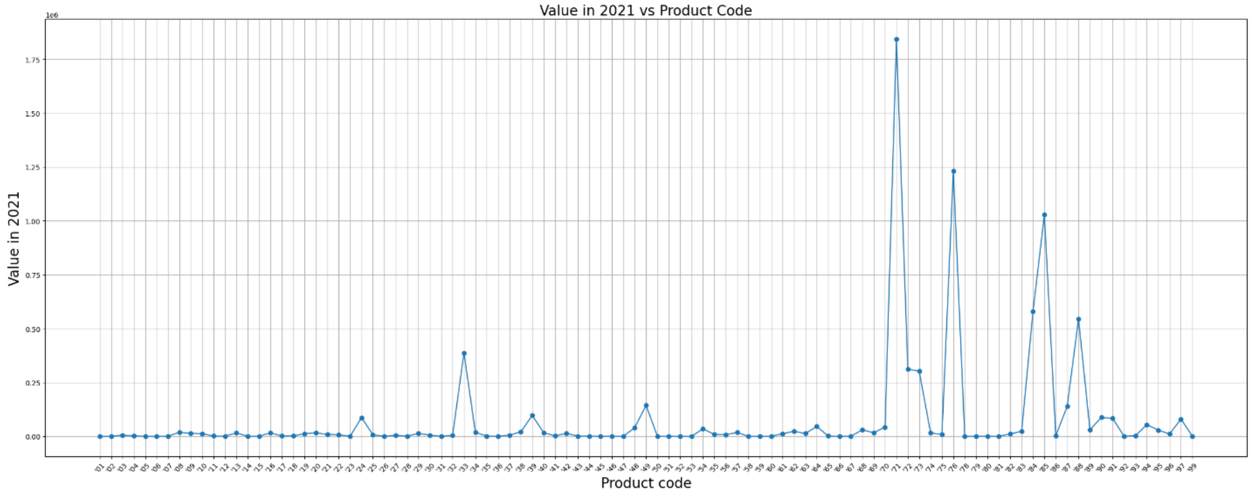
Figure 39: Trade value analysis of different products for 2015

Comparing these statistics with the graphs for the years 2020 and 2021, there is a huge difference in trade patterns in the UAE and the USA as shown in Figure 40 and Figure 41 respectively. Trade volume between these two nations increased significantly. The signing of the US-UAE Comprehensive Strategic Partnership Agreement in 2020, which is also expected to boost trade and investment between the two countries.




*(*All units are in Thousands USD)*

Figure 40: Trade value analysis of different products for 2020

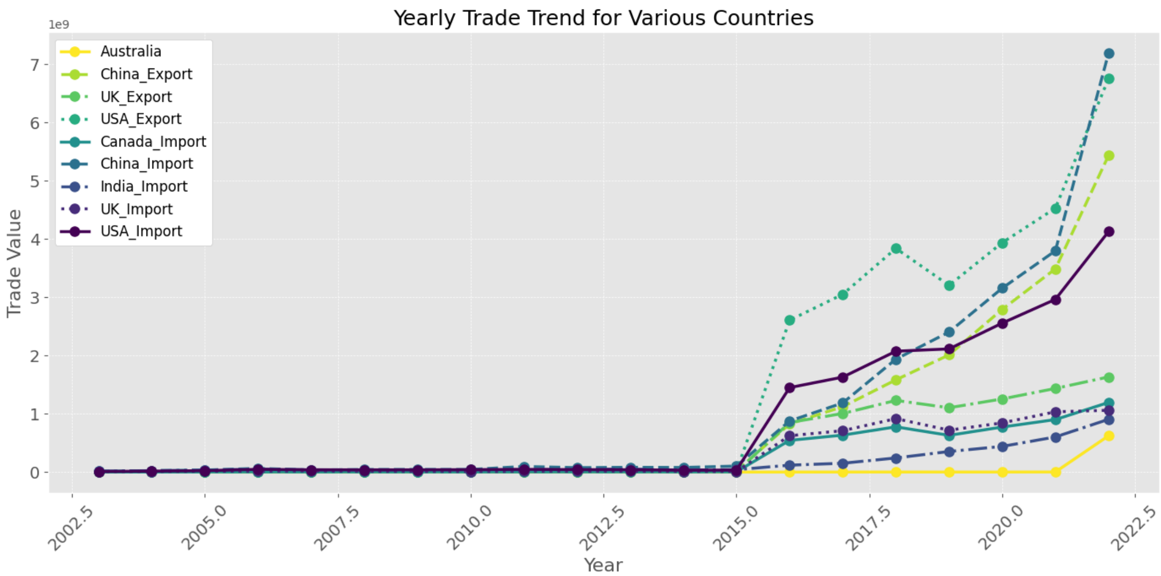



*(*All units are in Thousands USD)*

Figure 41: Trade value analysis of different products for 2021

## 4.2 Trade Trends with USA, UK, China, India and Australia

A comprehensive overview of the trade analysis conducted for the UAE is presented in Figure 42. It examines the dynamics of import and export between the UAE and its major trading partners, including the USA, China, UK, India, and Australia. As it provides a visual representation of both imports and exports, this figure is a useful tool for deficit analysis. The figure presents fascinating insights into trade relations between the UAE and these important countries. When analyzing the UAE's trade relations with the USA, exports to the USA far outweigh imports from that country. The dynamics of trade with China, however, show that there are significantly more imports from China than exports to China.




**(All units are in Thousands USD)*

Figure 42: Import and export analysis of UAE with different countries

Figure 42 captures a delicate depiction of the UAE's trade patterns, highlighting the interaction of imports and exports with important countries and opening the door for more thorough investigations in the field of international trade economics.

## 4.3 UAE Trade Analysis Under Changing Scenarios

The UAE is a global trade hub, and its trade patterns are influenced by a variety of factors, including economic conditions, government policies, technological changes, trade agreements, and exchange rates.

In recent years, the UAE has been working to diversify its economy and reduce its reliance on oil exports. This has led to an increase in non-oil exports, such as manufactured goods and services. The UAE has also become a major re-export hub.

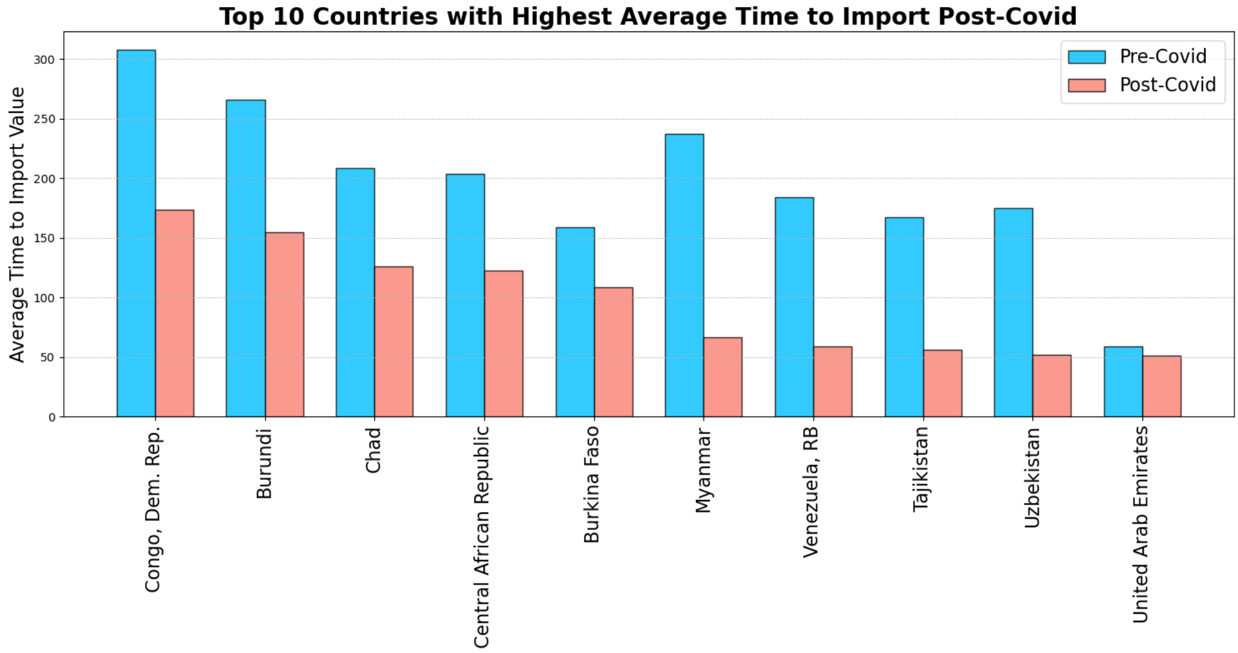
The UAE's trade is also influenced by its strategic location. The UAE is located at the crossroads of Europe, Asia, and Africa, and it has a modern and efficient transportation and logistics infrastructure. This makes the UAE an ideal location for businesses that want to trade with other countries in the region.

In this section, we analyze some of the scenarios and their implications and effects on UAE trade.

## 4.4 Time to Import Pre-COVID and Post-COVID

Before the COVID-19 pandemic, importing goods into the UAE used to take about 7-10 days on average that is slightly changed after COVID-19. Nowadays, it typically takes around 10-14 days. There's been a surge in the UAE's economy after the worst of the COVID-19 situation passed. People are buying more things from other countries, which means there's a lot more stuff coming in. This has made the whole process of bringing in goods slower because there's just so much more to handle.

The way goods move around the world got messed up by COVID-19. Ships and planes couldn't move as freely, and that caused delays. So, even if there's a strong demand for stuff in the UAE, it's taking longer for things to arrive.




*(All units are in Thousands USD)*

Figure 43: Pre and Post-COVID average time to import

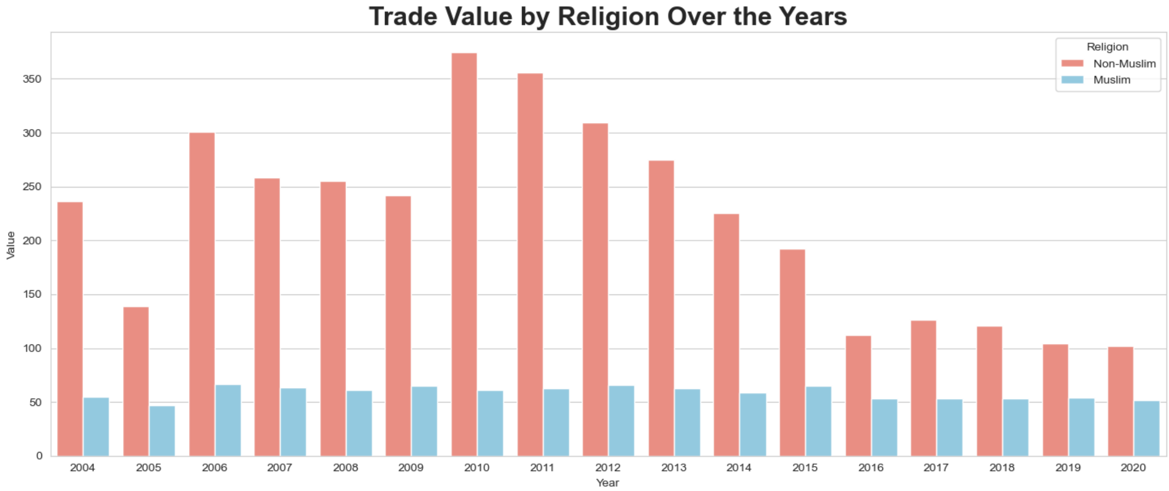
The UAE government is taking extra precautions to stop COVID-19 from spreading. This includes checking things carefully at ports, which, although necessary, slows things down.

Despite these delays, the UAE is still a big player in global trade. The government is determined to make importing stuff smoother and faster. They're putting money into better ports and smarter technology to keep the goods flowing.

However, as compared to the top ten countries in the world whose time to import is higher than UAE is shown in Figure 43.

### 4.5 Trade of UAE by Religion

In this section, we analyze the trade of UAE with the religious scenarios. We compared the trade of UAE over the years with Muslim and non-Muslim countries. Figure 44 shows the bar plot of UAE trade with Muslim and non-Muslim countries over the years.




*(All units are in Thousands USD)*

Figure 44: Trade of UAE by religion from 2004 to 2020

The code snippet to visualize Figure 44 is used for data manipulation and visualization using Python, with a focus on analyzing trade data by religion over the years.

- In the first step, we created the mapping dictionaries. Two dictionaries are created: `muslim_map` and `non_muslim_map`.
- `muslim_map` is a dictionary where each key represents a country (from the `muslim_countries` list), and the corresponding value is set to "Muslim".
- `non_muslim_map` is a dictionary where each key represents a country (from the `non_muslim_countries` list), and the corresponding value is set to "Non-Muslim".

In the next step, `all_religion_map` is created by combining the `muslim_map` and `non_muslim_map` dictionaries using the `**` operator. This results in a single dictionary where all countries are mapped to their respective religious categories (either "Muslim" or "Non-Muslim").

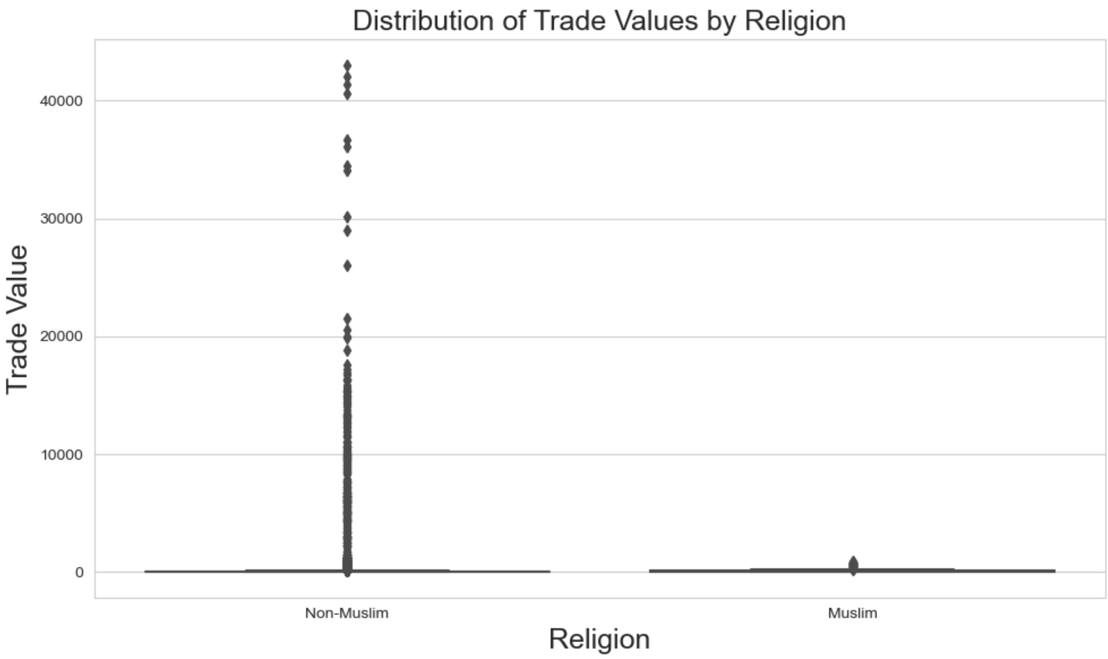
- The `df_melted` DataFrame is updated by adding a new column called "Religion".
- The "Religion" column is populated by mapping the values in the "Country Name" column of the DataFrame to the corresponding values in the

`all_religion_map`. This essentially assigns a religion (either "Muslim" or "Non-Muslim") to each country in the DataFrame.

For plotting the bar chart, A bar plot is created using the Seaborn library (`sns.barplot`).

- The x-axis represents the "Year," the y-axis represents the "Value" (which likely corresponds to trade values), and the hue (color) of the bars is determined by the "Religion" column.
- `The ci=None` argument specifies that no confidence intervals should be plotted.
- Custom colors are defined for the "Muslim" and "Non-Muslim" categories using the `palette` parameter.
- Titles and labels are added to the plot.
- The resulting plot is saved as an image file in a specified folder.

The trade distribution of UAE is shown in Figure 45. UAE has large trade values with both Muslim and Non Muslim countries. The trade of with Non Muslim countries is very large as compared to the Muslim Countries.




*(*All units are in Thousands USD)*

Figure 45: Trade distribution by religion.

The trade distribution of Muslim and non-Muslim countries with UAE is visualized using Python programming language. The first line imports the necessary libraries, including `plt` and `sns`. The second line specifies the figure size to be 12 inches by 7 inches. The third line creates a box plot using the `sns.boxplot()` function. The `sns.boxplot()` function takes the following arguments:

- `x`: The name of the column that contains the x-axis values.
- `y`: The name of the column that contains the y-axis values.
- `palette`: The color palette to use for the plot.
- The fourth line adds a title to the plot using the `plt.title()` function.
- The fifth line adds an x-axis label to the plot using the `plt.xlabel()` function.
- The sixth line adds a y-axis label to the plot using the `plt.ylabel()` function.
- The seventh line ensures that the plot is tightly laid out using the `plt.tight_layout()` function.
- The eighth line saves the plot to a file called boxplot_trade_by_religion.png using the `plt.savefig()` function.
- The ninth line displays the plot using the `plt.show()` function.

Results are the ultimate objective of scientific research: here you summarize the data collected and the statistical treatment of them. The observations and measurements recorded while conducting the procedures described in the methods section must address the questions raised in the introduction and any hypotheses formulated there. Overview of the main findings should be discussed in this section.

### 4.6 Evaluation of the Effectiveness of Regression Analysis in Predicting GDP and Evaluation of Trade Trends

In this section, we present a comprehensive exploration of the effectiveness of regression analysis as a powerful tool for forecasting the intricate relationship between a nation's Gross Domestic Product (GDP) and its import and export activities, while also assessing its capacity to predict evolving economic trends. The findings and methodologies employed shed light on the valuable role that regression analysis plays in aiding economic projections.

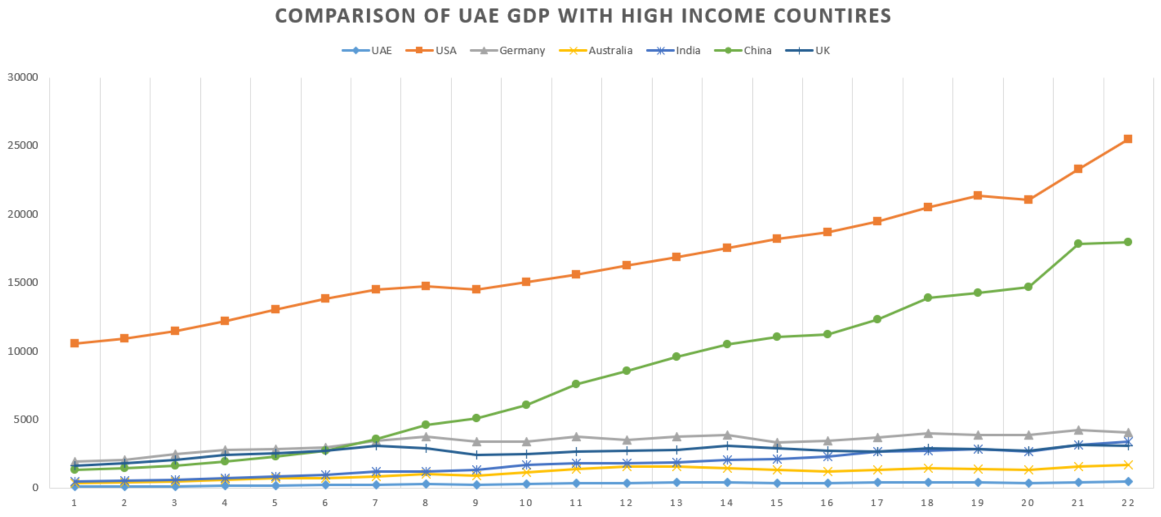
The regression analysis proved to be a robust method for unraveling the intricate interactions between a country's GDP and its trade dynamics. By scrutinizing historical data, our model provided a sound understanding of how fluctuations in exports and imports influenced GDP growth. The multiple regression model, incorporating export and import variables, offered an effective tool for estimating GDP changes based on trade activities. The lower Mean Squared Error (MSE) underscored the model's ability to provide accurate predictions.

An integral facet of our study was the model's ability to predict trends, particularly in the context of the UAE’s international trade. Utilizing time series data, the model successfully captured the dynamics of GDP and trade over various years. The inclusion of lagged variables allowed the model to anticipate future GDP and trade values, making it a valuable asset for governments and policymakers. The impressive correlation matrix affirmed that our predictions closely mirrored the actual data, attesting to the model's ability to discern and extrapolate economic trends.

### 4.7 Comparison of GDP of the UAE and other High-Income Countries

The United Arab Emirates (UAE) has experienced rapid economic growth in recent decades, and its GDP is now comparable to that of many other high-income countries. Figure 46 shows a comparison of the GDP of the UAE and other selected high-income countries. As the figure shows, the UAE has a comparable GDP than many other high-income countries, this is due in part to the UAE's reliance on oil and gas exports, which have generated significant revenue for the country.

It is important to note that the UAE's economy is relatively diversified, and the non-oil sector now accounts for around 70% of GDP. The UAE government has been investing heavily in infrastructure and education in recent years, and these investments are paying off. The UAE's high GDP per capita has led to a significant improvement in living standards for its citizens. The UAE now has a very high standard of living, with excellent healthcare, education, and infrastructure.



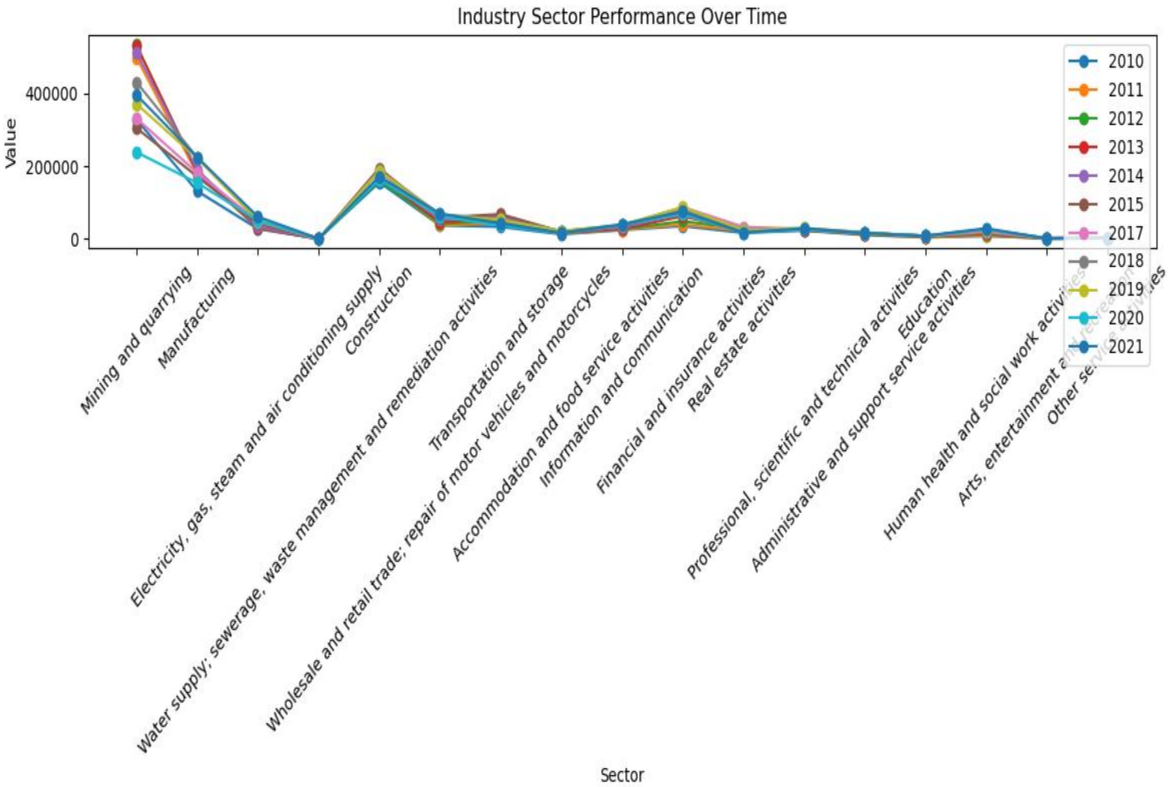

**(All units are in Billion USD)*

Figure 46: GDP of UAE and other high-income countries

# Chapter 5: Economic Analysis of Abu Dhabi

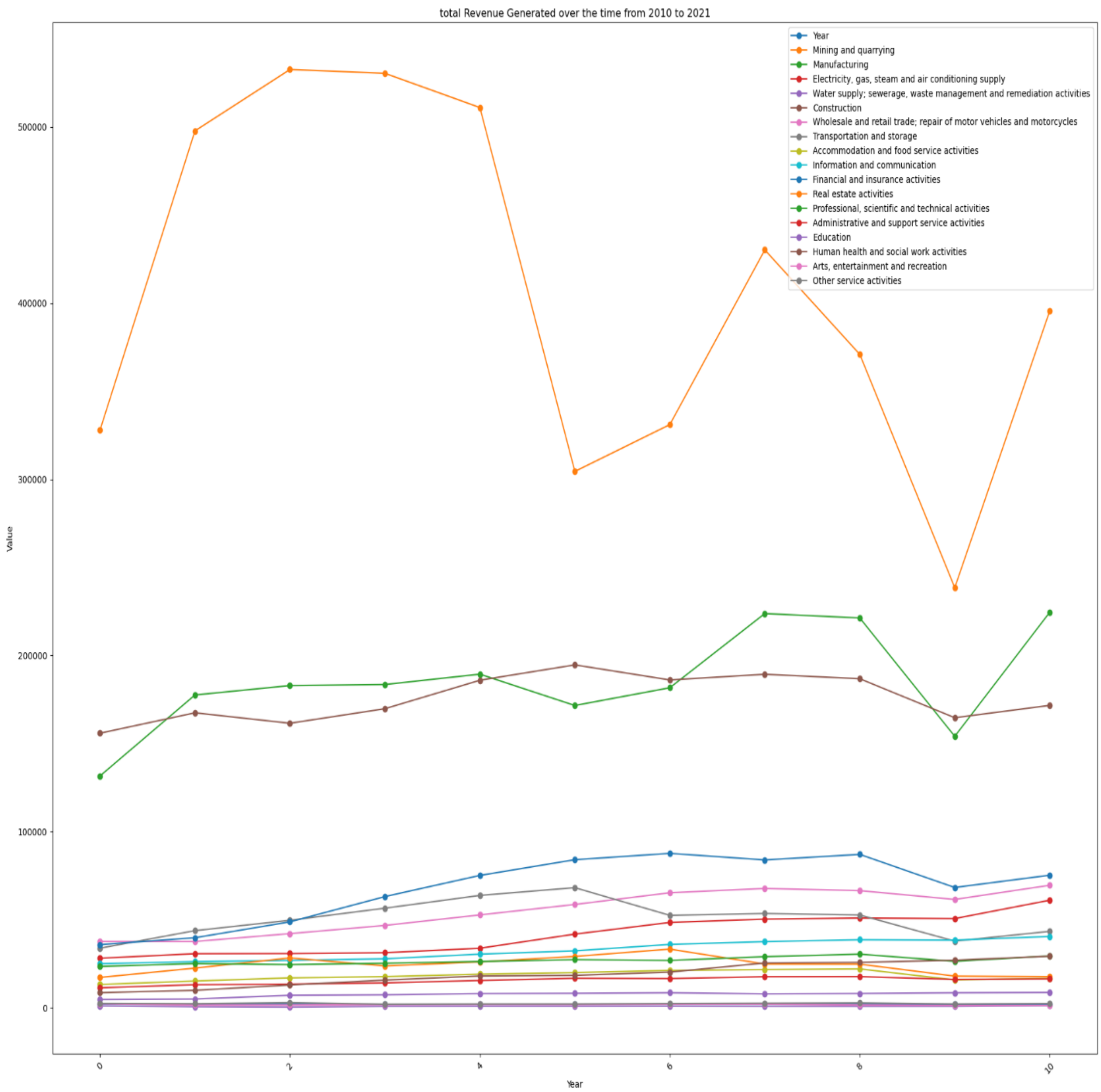
Abu Dhabi is the capital of the United Arab Emirates (UAE). It is a major center for trade, finance, and tourism. In the context of the country, Abu Dhabi plays a significant role in trade, accounting for over 50% of the country's total non-oil exports.

The economic analysis of Abu Dhabi from 2010 to 2021 shows that the emirate has experienced significant growth in different parameters like Number of establishments, Number of employees, Employee Compensation, Total Revenue, Intermediate consumption, Value Added, Gross fixed capital, and Depreciation. Figure 47 shows the revenue generated from the year 2010 to 2021 in different sectors. It shows a significant increase over the year in every sector.




*(All units are in Million AED)*

Figure 47: Revenue of Abu Dhabi in different sectors for 2010-2021




**(All units are in Million AED)*

Figure 48: Total revenue visualization in Abu Dhabi from 2010-2021

The line graph shown in Figure 48 shows the clear illustration of revenue generated in Abu Dhabi. It shows how the volume of revenue generated in Abu Dhabi progressed over the year. There is a decline in 2019 that can be attributed to COVID-19; however, a significant improvement has been made in generation of revenue after 2020. The top sector in generating revenue for Abu Dhabi is mining and quarrying, Manufacturing, and Electricity, gas and air condition supply. The trade analysis of Abu Dhabi in the context of the UAE shows that the emirate is a major contributor to the country's economy. Abu Dhabi has a large number of establishments and employees and generates a significant amount of revenue and value added. This analysis can be used to identify opportunities for businesses to expand into the Abu Dhabi market or to increase their trade with the emirate. For example, businesses could target the growing services sector in Abu Dhabi, or they could invest in new machinery and equipment to increase their production capacity.

The analysis can also be used to inform government policies aimed at promoting trade and economic growth in Abu Dhabi. A comprehensive confusion matrix is presented in Figure 49 below that shows the clear picture of revenue generated in each year.

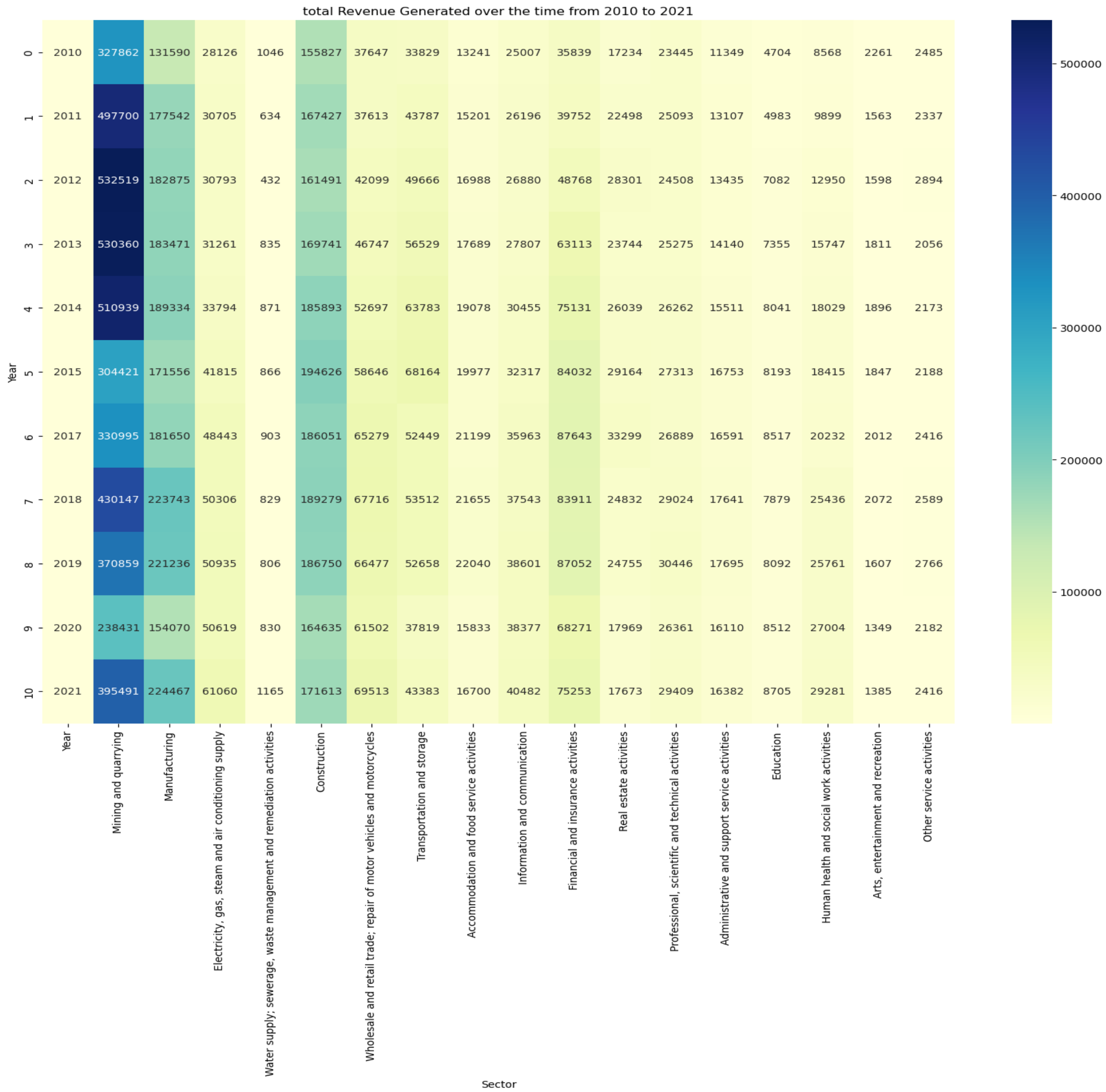


Figure 49: Correlation matrix of Abu Dhabi revenue in different sectors

# Chapter 6: Conclusion

## 6.1 Main Findings of the Study

- This analysis of the United Arab Emirates' (UAE) trade relations with major countries reveals key findings. The United States emerges as the UAE's primary trade partner, highlighting strong trade ties. China plays a pivotal role as the UAE's main importer, significantly contributing to the UAE's domestic market. The study also underscores the value of imports from the USA and significant exports to China. The UAE maintains a presence in the UK market, and various countries, including Canada, India, and Australia, contribute to its trade landscape. These findings shed light on the UAE's dynamic trade relationships and their importance in its global economic engagement.
- The analysis reveals that the UAE has significant trade growth prospects with various countries, including the UK and Australia, suggesting opportunities for expanding and diversifying export markets. Furthermore, the consistency in the UAE's trade relations with its top partners indicates mutual dependability and economic benefit. Understanding these trade balances is crucial, given the potential economic repercussions associated with recurring surpluses or deficits. Examining the data highlights the UAE's dependence on specific nations for imports, which carries implications for supply chain resilience and diversification. This information can inform strategies for market expansion and economic growth.
- The study's findings from the LSTM model and visualizations indicate a noteworthy trend in the United Arab Emirates' (UAE) trade. Despite global changes and various influencing factors, UAE's trade is steadily on the rise. The analysis reveals a linear upward trend in trade values over the years. While the growth rate is not exceptionally rapid, it suggests a consistent and positive trajectory. This trend is indicative of a stable and resilient trade environment, which has proven to be a key strength of the UAE's economy.
- One of the key conclusions drawn from this analysis is that the UAE has demonstrated its ability to maintain and even grow its trade activities over time, showing resilience in the face of economic challenges and external factors. This

stability in trade growth highlights the UAE's capacity to adapt and maintain economic stability, even in the presence of global economic fluctuations, such as the impact of the COVID-19 pandemic. Additionally, the efforts to diversify the economy and reduce reliance on oil exports have contributed to the positive trade patterns observed. These findings underscore the UAE's proactive economic strategies and its position as a reliable player in international trade.

- This analysis offers a visual tool for assessing trade imbalances, revealing intriguing insights. To underscore the importance of understanding trade dynamics with key partners, providing valuable insights for policymakers and businesses seeking to navigate the complexities of global trade, and for those looking to apply similar methodologies or examine deeper into trade analysis, detailed Python code snippets for analyzing and visualizing trade analysis are provided.
- Geographically, the UAE's prime location at the intersection of Europe, Asia, and Africa, bolstered by its advanced transportation and logistics infrastructure, fortifies its status as a preeminent hub for international trade. This analysis explores diverse scenarios and their impacts on UAE trade dynamics.
- The study highlights how COVID-19 has affected the import timeline, extending it from the pre-pandemic average of 7-10 days to around 10-14 days post-COVID. The UAE's resilient economic bounce-back has led to increased imports, resulting in slower processing due to the heightened volume. The global movement of goods was disrupted, with shipping and flight restrictions causing delays, despite robust demand.

## 6.2 Recommendations to Improve Trade Forecasting

As the conclusion of this study, we are giving some recommendations to improve the accuracy of trade forecasting in the UAE:

### *6.2.1 Use a Variety of Forecasting Methods*

There is no single forecasting method that is always the most accurate. It is important to use different forecasting models and compare the results of those models. Using a variety of methods and comparing the results to get a more complete picture is very important in forecasting.

### *6.2.2 Use High-Quality Data*

Whatever the model is, the most important thing is the data. The accuracy of a forecast depends on the quality of the data used in the training of any model. Therefore, it is crucial to use data that is reliable, up-to-date, and relevant to the forecast. The authenticity of the data must be fulfilled before training a model.

### *6.2.3 Consider a Variety of Factors*

Forecasting a trade analysis, particularly for a country that has a diverse culture, diverse economy, and a wide range of factors for example for the UAE, many factors can affect trade, including economic conditions, government policies, and technological changes. Therefore, it is very important to consider a variety of factors when forecasting trade. These factors can affect the trade analysis.

### *6.2.4 Update Forecasts Regularly*

As discussed, there could be many factors that can affect the trade analysis of a country. Forecasts should be updated regularly to reflect changes in the economic and trade environment. This will help in improving the accuracy of the forecasting model.

### *6.2.5 Use Expert Judgment*

The prediction of forecasting models can be affected due to rapid changes in technology and continuous changes in government policies. Therefore, expert judgment can be used to supplement the results of statistical forecasting methods. Experts can provide a better understanding of factors that may be difficult to quantify, such as the impact of government policies or technological changes.

## 6.3 Main Factors that Influence the Trade of UAE

There are various factors we analyzed during the experimentations of this thesis. These factors influence the trade of UAE. A few factors are elaborated below.

### *6.3.1 Oil Prices*

The UAE is a major exporter of oil and gas. As a result, oil prices have a significant impact on the UAE's trade balance. When oil prices are high, the UAE's trade balance improves. When oil prices are low, the UAE's trade balance deteriorates. As we have observed during COVID-19. The exports of UAE decreased for example for HS 27 during the pandemic. This affects the overall economy of UAE.

### *6.3.2 Non-Oil Exports*

The UAE has been working to expand its economy and reduce its reliance on oil exports. As a result, non-oil exports, such as manufactured goods and services, have become increasingly important to the UAE's economy.

### *6.3.3 Re-Exports*

The UAE is a major re-export hub. The UAE imports goods from other countries and then re-exports them to other countries. Re-exports are an important source of revenue for the UAE.

### *6.3.4 Tourism*

Tourism is a important and swiftly growing sector in the United Arab Emirates (UAE) economy. The country has made significant investments in developing its tourism infrastructure, including luxurious hotels, entertainment facilities, and world-class attractions. These investments have yielded substantial returns, attracting tourists from all corners of the globe. The revenue generated from tourism substantially contributes to the country's Gross Domestic Product (GDP) and plays a paramount role in the UAE's economic diversification efforts. Notably, the UAE has been actively working to diversify its economy away from its historical reliance on oil, and tourism has emerged as one of the key pillars in achieving this goal. The UAE features a wide range of tourist attractions, making it a sought-after destination. The UAE offers visitors a blend of both traditional and modern experiences, ranging from exploring historic souks to indulging in high-end shopping, theme parks, and world-class entertainment.

The economic impact of tourism in the UAE is considerable. Several sectors benefit directly from this industry, including the hospitality sector, retail industry, transportation, and various services. Hotels, restaurants, and shopping malls profit directly from the influx of tourists, creating numerous employment opportunities and stimulating the local economy. The hospitality sector stands out as a significant beneficiary as it caters to the diverse needs and preferences of tourists. Furthermore, the goods and services relevant to the tourism industry encompass a wide range, including everything from food and beverages to construction materials used for building hotels and attractions. The UAE maintains a robust supply chain to support the tourism sector, which involves importing goods and services, thereby promoting economic activity.

## References

Al Mesfer, A. S. (2023). *Forecast-Driven Inventory Management for the Fast-Moving Consumer Goods Industry* (Doctoral dissertation, Massachusetts Institute of Technology).

Balaji, A. J., Ram, D. H., & Nair, B. B. (2018). Applicability of deep learning models for stock price forecasting an empirical study on BANKEX data. *Procedia computer science*, *143*, 947-953.

Baldwin, J. R., & Gu, W. (2005). Global links: multinationals, foreign ownership and productivity growth in Canadian manufacturing. *Canadian Economy in* Transition *Working Paper*.

Barbaglia, L., Consoli, S., & Manzan, S. (2023). Forecasting with economic news. *Journal of Business & Economic Statistics*, *41*(3), 708-719.

Bartos, M. D., Mullapudi, A., & Troutman, S. C. (2019). rrcf: Implementation of the robust random cut forest algorithm for anomaly detection on streams. *Journal of Open Source Software*, *4*(35), 1336.

Breiman, L. (2001). Random forests. *Machine learning*, *45*, 5-32.

Caruana, R., Lou, Y., Gehrke, J., Koch, P., Sturm, M., & Elhadad, N. (2015, August). Intelligible models for healthcare: Predicting pneumonia risk and hospital 30-day readmission. In *Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 1721-1730).

Chaziza, M. (2019). *China and the Persian Gulf: The new Silk Road Strategy and Emerging Partnerships*. Liverpool University Press.

Dollar, D., & Kraay, A. (2003). Institutions, trade, and growth. *Journal of Monetary Economics*, *50*(1), 133-162.

Dumor, K., & Yao, L. (2019). Estimating China’s trade with its partner countries within the Belt and Road Initiative using neural network analysis. *Sustainability*, *11*(5), 1449.

Edwards, S. (1998). Openness, productivity and growth: what do we really know?. *The Economic Journal*, *108*(447), 383-398.

Estrella, A., & Mishkin, F. S. (1998). Predicting US recessions: Financial variables as leading indicators. *Review of Economics and Statistics*, *80*(1), 45-61.

Ewers, M. C., Khattab, N., Babar, Z., & Madeeha, M. (2022). Skilled migration to emerging economies: The global competition for talent beyond the West. *Globalizations*, *19*(2), 268-284.

Frankel, J. A., & Romer, D. (2017). Does trade cause growth?. In *Global trade* (pp. 255-276). Routledge.

Gavran, T. (2019). Stani Stanko. *Osvit*, (97-98), 46-47.

GEP, J. B. (1970). Time series analysis, forecasting and control, holden-day. *San Francisco, CA*.

Geurts, M. (1977). Book review: time series analysis: forecasting and control.

Giannone, D., Reichlin, L., & Small, D. (2008). Nowcasting: The real-time informational content of macroeconomic data. *Journal of Monetary Economics*, *55*(4), 665-676.

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, *14*(2), 627-660.

Hedström, A., Zelander, N., Junttila, J., & Uddin, G. S. (2020). Emerging market contagion under geopolitical uncertainty. *Emerging Markets Finance and Trade*, *56*(6), 1377-1401.

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural computation*, *9*(8), 1735-1780.

Ismail, L., Alhmoudi, S., & Alkatheri, S. (2020, December). Time series forecasting of COVID-19 infections in United Arab Emirates using ARIMA. In *2020 International Conference on Computational Science and Computational Intelligence (CSCI)* (pp. 801-806). IEEE.

Javed, I., Ashfaq, M., Adil, S. A., & Bakhsh, K. (2016). Analysis of agricultural trade between Pakistan and United Arab Emirates: an application of gravity model. *Journal of Agricultural Research (03681157)*, *54*(4).

Joo, H. Y., & Lee, D. J. (2021). A study on the prediction model for international trade payment using logistic regression. *Journal of Korea Trade*, *25*(2), 111-133.

Kleemann, L., & Abdulai, A. (2013). The impact of trade and economic growth on the environment: Revisiting the cross-country evidence. *Journal of International Development*, *25*(2), 180-205.

Koop, G., Korobilis, D., & Pettenuzzo, D. (2019). Bayesian compressed vector autoregressions. *Journal of Econometrics*, *210*(1), 135-154.

Lee, H. Y., Ricci, L. A., & Rigobon, R. (2004). Once again, is openness good for growth?. *Journal of Development Economics*, *75*(2), 451-472.

Linnemann, H. (1966). An econometric study of international trade flows. *(No Title)*.

Nabipour, M., Nayyeri, P., Jabani, H., Mosavi, A., & Salwana, E. (2020). Deep learning for stock market prediction. *Entropy*, *22*(8), 840.

Peersman, G. (2004). The transmission of monetary policy in the Euro Area: are the effects different across countries?. *Oxford Bulletin of Economics and Statistics*, *66*(3), 285-308.

Rana, S., & Shrivastavais, A. K. Doing Business in Emerging Markets.

Raza, W., Taylor, L., Tröster, B., & von Arnim, R. (2016). *Modelling The impacts of Trade on Employment and Development: A Structuralist CGE-Model for the Analysis of TTIP and Other Trade Agreements* (No. 57). ÖFSE Working Paper.

Reynolds, D. B., & Umekwe, M. P. (2019). Shale-oil development prospects: The role of shale-gas in developing shale-oil. *Energies*, *12*(17), 3331.

Rodriguez, F., & Rodrik, D. (2000). Trade policy and economic growth: a skeptic's guide to the cross-national evidence. *NBER macroeconomics annual*, *15*, 261-325.

Schwarz, R. (2008). The political economy of state-formation in the Arab Middle East: Rentier states, economic reform, and democratization. *Review of International Political Economy*, *15*(4), 599-621.

Sen, A., & Dutta Choudhury, K. (2022). A case study of Gulf Securities Market in the last 20 years: An LSTM approach. *Statistica Neerlandica*.

Shrivastava, V. K., & Riaz, S. (2022, March). Business Development Using Big Data within UAE SMEs Retail Sector: Prospects & Questions. In *2022 14th International Conference on Computer and Automation Engineering (ICCAE)* (pp. 145-150). IEEE.

Siiner, M. (2016). *Oil Dependency: To what extent is the United Arab Emirates Economy Dependent on Natural Resources?*. Tallinn University of Technology, Estonia.

Singh, S. K., & El-Kassar, A. N. (2019). Role of big data analytics in developing sustainable capabilities. *Journal of cleaner production*, *213*, 1264-1273.

Sturm, M., Strasky, J., Adolf, P., & Peschel, D. (2008). *The Gulf Cooperation Council countries-economic structures, recent developments and role in the global economy*. *ECB Occasional Paper Series*. Retrieved March 26, 2023, from https://www.ecb.europa.eu/pub/pdf/scpops/ecbocp92.pdf

Tang, Y., Song, Z., Zhu, Y., Yuan, H., Hou, M., Ji, J., ... & Li, J. (2022). A survey on machine learning models for financial time series forecasting. *Neurocomputing*, *512*, 363-380.

WTO (2021). *Global trade rebound beats expectations but marked by regional divergences*. Retrieved March 15, 2023, from https://www.wto.org/english/news_e/pres21_e/pr889_e.htm

Zhang, L., Aggarwal, C., & Qi, G. J. (2017, August). Stock price prediction via discovering multi-frequency trading patterns. In *Proceedings of the 23rd ACM SIGKDD international conference on knowledge discovery and data mining* (pp. 2141-2149).

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Exploring the impact of trade on the United Arab Emirates' economic growth using LSTM neural networks. By forecasting GDP based on historical trade data, the study reveals intricate trade patterns and their effects. The innovative use of LSTM models, Beyond contributing to economic analysis, the research advocates for the integration of artificial intelligence, machine learning, and cryptography to enhance our understanding of the global economic landscape while ensuring security and confidentiality. Emphasizing the potential for intelligent computational techniques to guide decision-making in international trade and economic development, the thesis offers valuable insights into predictive economic analysis and policy-making

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