DETAILED PROJECT REPORT (DPR)

Analysing International Debt Statistics (IDS)

A WORLD OF DEBT

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TABLE OF CONTENT

Executive Summary

The data analysis project titled "Analysing International Debt Statistics (IDS)" aims to explore and derive insights from debt data collected by The World Bank. The primary purpose is to understand the patterns and trends in international debt, providing valuable information for economic analysis and decision-making. The key objectives include determining the total amount of debt owed by countries, identifying the country with the highest debt, and calculating the average debt across various indicators.

By leveraging Python for in-depth analysis and Power BI for visualization, the project offers a dynamic and user-friendly International Debt Statistics (IDS) Dashboard. This dashboard includes interactive elements such as slicers for country name, country code, series code, and sector, ensuring a personalized exploration of the data. Top cards, maps, race charts, and line charts present a comprehensive overview of total debt, principal repayments, and debt trends from 1970 to 2030.

The expected outcomes include actionable insights for policymakers, economists, and stakeholders involved in international finance. The project contributes to a better understanding of global debt dynamics, facilitating informed decision-making and strategic planning. Future enhancements may involve exploring additional dimensions of analysis and further refining the user interface for a richer and more interactive experience.

The collaborative use of Python and Power BI in this project exemplifies the integration of advanced analytical techniques with powerful visualization tools, underscoring the project's commitment to delivering meaningful and accessible insights into international debt statistics.

1. Introduction

1.1 Background and Context

The "Analysing International Debt Statistics (IDS)" project emerges from the critical role that debt plays in managing a country's economy, particularly in funding essential infrastructure. As humans seek financial assistance for their necessities, countries turn to organizations like The World Bank. This project delves into international debt data collected by The World Bank, focusing on understanding debt dynamics from 1970 to 2030. The analysis aims to uncover patterns, trends, and key insights that contribute to informed decision-making in the realm of global finance.

1.2 Project Objectives

The primary objectives of this project include:

- Determining the total amount of debt owed by countries listed in the dataset.
- Identifying the country with the highest debt and quantifying the amount.
- Calculating the average debt owed by countries across various debt indicators.

These objectives serve as a roadmap for extracting meaningful insights from the dataset and addressing key questions related to international debt.

1.3 Scope and Limitations

Scope

The project scope encompasses:

- Utilizing Python for in-depth analysis.
- Creating an interactive dashboard using Power BI for visualization.
- Examining debt data from The World Bank covering the period 1970 to 2030.
- Addressing key questions about total debt, highest debt, and average debt.

Limitations

While the project endeavours to provide comprehensive insights, certain limitations include:

- Reliance on available data from The World Bank.
- Potential gaps or inaccuracies in the dataset.
- Constraints imposed by the scope and timeframe of the project.

Understanding these limitations is crucial for interpreting the results accurately and managing expectations.

2. Ask Stage

2.1 Problem Statement

The global economic landscape involves countries managing their economies through strategic debt utilization. Infrastructure spending, a vital aspect for citizens' well-being, often demands significant financial resources. The World Bank, as a key financial institution, facilitates countries in obtaining necessary debts. This project addresses the crucial problem of understanding and analysing international debt data provided by The World Bank. The dataset encompasses information on the USD amount of debt owed by developing countries, covering various categories. Key questions to be addressed include determining the total debt owed, identifying the country with the highest debt, and calculating the average debt across different indicators.

2.2 Need Assessment

The need for this analysis arises from the importance of comprehending the global debt landscape. By assessing international debt data, policymakers, economists, and stakeholders gain valuable insights into economic trends and challenges. Understanding the total debt, highest debtor, and average debt by indicators equips decision-makers with the information necessary for effective economic planning and resource allocation.

2.3 Project Proposal

Project Tasks

1. **The World Bank's International Debt Data:**

   Collect and explore the provided international debt dataset from The World Bank.

2. **Finding the Number of Distinct Countries:**

   Identify and analyze the distinct countries included in the dataset.

3. **Finding Out Distinct Debt Indicators:**

   Explore and categorize the distinct debt indicators present in the dataset.

4. **Totalling the Amount of Debt Owed by Countries:**

   Calculate the total amount of debt owed by the countries listed in the dataset.

5. **Country with the Highest Debt:**

   Determine the country that owns the maximum amount of debt and quantify the amount.

6. **Average Amount of Debt Across Indicators:**

   Calculate and analyze the average amount of debt owed by countries across different debt indicators.

7. **The Highest Principal Repayments Amount:**

   Identify the country with the highest principal repayments amount.

8. **The Most Common Debt Indicator:**

   Determine the most common debt indicator among the countries.

9. **Other Viable Debt Issues and Conclusion:**

   Explore additional viable debt-related issues and provide a comprehensive conclusion.

The proposed tasks lay the foundation for a detailed analysis that addresses key questions and contributes to a nuanced understanding of international debt dynamics.

3. Prepare Stage

3.1 Project Planning

3.1.1 Project Title and Description

Project Title: Analysing International Debt Statistics
Description: This project aims to delve into The World Bank's international debt dataset, exploring the indebtedness landscape of developing countries. Through data analysis and visualization, it seeks to derive insights into total debt, identify the highest debtor, and calculate average debts across various indicators.

3.1.2 Project Timeline

- Phase 1: Data Exploration (2 weeks)
    - Collect and clean The World Bank's international debt data.
    - Perform preliminary exploratory data analysis (EDA).
- Phase 2: Analysis and Visualization (4 weeks)
    - Conduct in-depth analysis using Python.
    - Create interactive visualizations in Power BI.
- Phase 3: Report and Documentation (2 weeks)
    - Summarize findings in a detailed report.
    - Prepare High-Level Design (HLD) and Low-Level Design (LLD) documents.

3.2 Resource Allocation

3.2.1 Human Resources

- Data Analysts (1):
    - Responsible for data cleaning, analysis, and visualization.
- Project Manager (1):
    - Oversee project progress, coordinate tasks, and ensure timelines are met.
- Subject Matter Expert (1):
    - Provide insights into economic indicators and debt-related nuances.

3.2.2 Financial Resources

- Software and Tools:
    - Allocate budget for licenses of Python, Power BI, and necessary libraries.
- Training and Skill Development:
    - Provide resources for training on advanced data analysis techniques.

3.3 Risk Assessment

3.3.1 Identification of Risks

1. Data Quality Issues:
    - Risk: Incomplete or inaccurate data may affect analysis.
    - Likelihood: Moderate
    - Impact: High
    - Mitigation: Implement thorough data cleaning and validation processes.
2. Resource Constraints:
    - Risk: Unavailability of key resources.
    - Likelihood: Low
    - Impact: Moderate
    - Mitigation: Develop contingency plans and cross-train team members.
3. Technical Challenges:
    - Risk: Technical issues during data analysis.
    - Likelihood: Moderate
    - Impact: Moderate
    - Mitigation: Regularly update tools and seek technical support when needed.

3.3.2 Mitigation Strategies

- Data Quality Assurance:
    - Implement rigorous data validation processes.
    - Collaborate with data providers to address any discrepancies.
- Resource Management:
    - Cross-train team members to ensure flexibility.
    - Regularly review resource allocation against project requirements.
- Technical Support:
    - Establish communication channels with technical support services.
    - Keep software and tools up-to-date to mitigate potential technical issues.

4. Process Stage

4.1 Methodology

4.1.1 Data Collection

The data collection process involves obtaining The World Bank's international debt dataset. The dataset spans from 1970 to 2030 and includes both national and regional debt statistics for various countries. The data is acquired from the provided link and is essential for conducting a comprehensive analysis of international debt.

4.1.2 Tools and Technologies

To facilitate effective data analysis and visualization, the following tools and technologies will be employed:

- **Python:**
  - Utilize Python programming language for data analysis tasks.
  - Leverage Jupyter Notebooks along with libraries such as Pandas and NumPy.
- **Power BI:**
  - Import cleaned and analysed data into Power BI for visualization.
  - Develop interactive dashboards to represent key findings visually.

4.2 Data Description

4.2.1 Source and Structure

The dataset is provided by The World Bank and includes information on the amount of debt (in USD) owed by developing countries. The data covers various categories and is recorded annually from 1970 to 2030. It encompasses both national and regional debt statistics, offering a comprehensive view of international debt dynamics.

Dataset:

The World Bank. (2023). International Debt Statistics (IDS) Dataset Version 7. Retrieved from **World Bank Data Catalog.**

Version: 7, Metadata last updated on - Dec 15, 2023

International Debt Statistics (IDS), successor to Global Development Finance and World Debt Tables, is designed to respond to user demand for timely, comprehensive data on trends in external debt in low- and middle-income countries. The World Bank's Debtor Reporting System (DRS), from which the aggregate and country tables presented in this report are drawn, was established in 1951. World Debt Tables, the first publication that included DRS external debt data, appeared in 1973 and gained increased attention during the debt crisis of the 1980s. Since then, the publication and data have undergone numerous revisions and iterations to address the challenges and demands posed by the global economic conditions.

The source of the data is the CSV file named 'IDS_ALLCountries_Data.csv', provided by The World Bank. The data is loaded into a Pandas Data Frame using the pd.read_csv function in Python. The encoding parameter is set to 'ISO-8859-1' to handle any character encoding issues that might be present in the data.

```
import pandas as pd
import plotly.express as px
import plotly.io as pio

# Set the default template to 'plotly_dark'
pio.templates.default = "plotly_dark"

# Read the raw data from the provided CSV file
world_raw_data = pd.read_csv('IDS_ALLCountries_Data.csv', encoding='ISO-8859-1')
```

To gain an initial understanding of the dataset's structure and content, the code snippet above uses the head() function to display the first few rows of the loaded data in the 'world_bank_country' DataFrame. This step is crucial in the data analysis process as it allows for a quick examination of the dataset's columns, data types, and the overall format of the information.

```
# Display the first few rows of the loaded data for initial exploration
world_raw_data.head()
```

	Country Name	Country Code	Counterpart-Area Name	Counterpart-Area Code	Series Name	Series Code	1970	1971	1972	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983	198
0	Afghanistan	AFG	World	WLD	Average grace period on new external debt comm...	DT.GPA.DPPG	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
1	Afghanistan	AFG	World	WLD	Average grace period on new external debt comm...	DT.GPA.OFFT	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
2	Afghanistan	AFG	World	WLD	Average grace period on new external debt comm...	DT.GPA.PRVT	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
3	Afghanistan	AFG	World	WLD	Average grant element on new external debt com...	DT.GRE.DPPG	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
4	Afghanistan	AFG	World	WLD	Average grant element on new external debt com...	DT.GRE.OFFT	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na

```
# You can use the ~ operator with isin() to filter out the specified values
world_bank_country = world_raw_data[~world_raw_data['Country Code'].isin(['EAP', 'ECA', 'IDX', 'IDA', 'LAC',
'LDC', 'LMY', 'LIC', 'LMC', 'MNA', 'MIC', 'SAS', 'SSA', 'UMC'])].copy()

# Now 'filtered_data' contains rows where 'Country Code' is not in the specified list
```

4.2.2 Cleaning and Pre-processing

Prior to analysis, the dataset undergoes thorough cleaning and pre-processing to ensure data quality and reliability. Key steps include:

```
# Select columns from '1970' to '2030'
selected_columns = world_bank_country.loc[:, '1970':'2030']

# Calculate the total debt for each country in trillion USD
world_bank_country['Total (Trillion USD)'] = selected_columns.sum(axis=1) / 1e12  # Convert to trillion

# Round values to four decimal places
world_bank_country[selected_columns.columns] /= 1e12  # Convert selected columns to trillion
world_bank_country['Total (Trillion USD)'] = world_bank_country['Total (Trillion USD)']

# Assign the modified DataFrame to a new variable 'world_bank_data'
world_bank_data = world_bank_country

# Round total to four decimal places
world_bank_data = world_bank_data.round(4)

# Fill missing values with zeros in the 'world_bank_data' DataFrame
world_bank_data.fillna(0, inplace=True)

# Display the modified DataFrame
world_bank_data.tail()
```

The above code snippet represents the cleaning and pre-processing steps for the international debt data. It involves selecting the relevant columns from '1970' to '2030', calculating the total debt in trillion USD, rounding the values to four decimal places, and filling any missing values with zeros. The resulting DataFrame, named 'world_bank_data', is now ready for further analysis and visualization.

Including this code in the Detailed Project Report (DPR) documents the crucial pre-processing steps, ensuring transparency and reproducibility in the data analysis process.

	Country Name	Country Code	Counterpart-Area Name	Counterpart-Area Code	Series Name	Series Code	1970	1971	1972	1973	1974	1975	1976	1977	1978	1979	
77787	Zimbabwe	ZWE	World	WLD	Undisbursed external debt, official creditors ...	DT.UND.OFFT.CD	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.000000	0.00
77788	Zimbabwe	ZWE	World	WLD	Undisbursed external debt, private creditors (...	DT.UND.PRVT.CD	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000005	0.000048	0.00
77789	Zimbabwe	ZWE	World	WLD	Undisbursed external debt, total (UND, current...	DT.UND.DPPG.CD	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000005	0.000048	0.00
77790	Zimbabwe	ZWE	World	WLD	Use of IMF credit (DOD, current US$)	DT.DOD.DIMF.US.CD	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.000000	0.00
77791	Zimbabwe	ZWE	World	WLD	Use of IMF credit and SDR allocations (DOD, cu...	DT.DOD.DIMF.CD	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.000000	0.00

- **Handling Missing Values:**
    - Identify and address any missing values in the dataset.
    - Utilize appropriate imputation methods based on the nature of missing data.

```
# Checking for missing values in the 'world_bank_data' DataFrame
print(f"\nCount of missing values in 'world_bank_data' DataFrame: {world_bank_data.isnull().sum().sum()}")
```

```
Count of missing values in world_bank_data df: 0
```

- **Duplicate Values:**
    - Detect and remove duplicate entries to maintain data integrity.

```
# Checking for duplicated values:
print(f"\nCount of duplicated values in world_bank_data df: {world_bank_data.duplicated().sum().sum()}")
```

```
Count of duplicated values in world_bank_data df: 0
```

The cleaning and pre-processing phase aims to prepare the dataset for meaningful analysis, addressing any issues that might impact the accuracy of the results.

5. Analyze Stage

5.1 Exploratory Data Analysis (EDA)

5.1.1 Dataset Overview

```
# Displaying the shape of the 'world_bank_data' DataFrame
print(f"Shape of world_bank_data: {world_bank_data.shape}\n")

# Displaying the columns in the 'world_bank_data' DataFrame
print(f"Columns in world_bank_data: {world_bank_data.columns}\n")

# Displaying information about the 'world_bank_data' DataFrame
print("Information about world_bank_data:")
world_bank_data.info()

# Displaying the first few rows of the 'world_bank_data' DataFrame
print("\nFirst few rows of world_bank_data:")
print(world_bank_data.head())
```

These code snippets provide essential insights during the exploratory data analysis (EDA) stage:

- Shape of the DataFrame: Indicates the number of rows and columns in the dataset.
- Columns in the DataFrame: Lists all the columns present in the dataset.
- Information about the DataFrame: Offers details about data types, non-null counts, and memory usage.
- First few rows of the DataFrame: Displays a snapshot of the dataset to understand its structure and content.

5.1.2 Insights from EDA

- The dataset consists of [Number of Rows] rows and [Number of Columns] columns.
- The columns [List of Columns] provide information on various aspects of international debt.
- The data types, non-null counts, and memory usage are detailed in the DataFrame information.

```
Shape of 'world_bank_data' DataFrame: (69784, 68)

Columns of 'world_bank_data' DataFrame: Country Name, Country Code, Counterpart-Area Name, Counterpart-Area Code, Series Name, Series Code, 1970, 1971, 1972, 197
3, 1974, 1975, 1976, 1977, 1978, 1979, 1980, 1981, 1982, 1983, 1984, 1985, 1986, 1987, 1988, 1989, 1990, 1991, 1992, 1993, 1994, 1995, 1996, 1997, 1998, 1999, 200
0, 2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023, 2024, 2025, 2026, 202
7, 2028, 2029, 2030, Total (Trillion USD)

Information about 'world_bank_data' DataFrame:
<class 'pandas.core.frame.DataFrame'>
Index: 69784 entries, 0 to 77791
Data columns (total 68 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Country Name           69784 non-null  object
 1   Country Code           69784 non-null  object
 2   Counterpart-Area Name  69784 non-null  object
 3   Counterpart-Area Code  69784 non-null  object
 4   Series Name            69784 non-null  object
 5   Series Code            69784 non-null  object
 6   1970                   69784 non-null  float64
 7   1971                   69784 non-null  float64
 8   1972                   69784 non-null  float64
 9   1973                   69784 non-null  float64
 10  1974                   69784 non-null  float64
 11  1975                   69784 non-null  float64
 12  1976                   69784 non-null  float64
 13  1977                   69784 non-null  float64
 14  1978                   69784 non-null  float64
 15  1979                   69784 non-null  float64
 16  1980                   69784 non-null  float64
 17  1981                   69784 non-null  float64
 18  1982                   69784 non-null  float64
 19  1983                   69784 non-null  float64
 20  1984                   69784 non-null  float64
 21  1985                   69784 non-null  float64
 22  1986                   69784 non-null  float64
 23  1987                   69784 non-null  float64
 24  1988                   69784 non-null  float64
 25  1989                   69784 non-null  float64
 26  1990                   69784 non-null  float64
 27  1991                   69784 non-null  float64
 28  1992                   69784 non-null  float64
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 58  2022                   69784 non-null  float64
 59  2023                   69784 non-null  float64
 60  2024                   69784 non-null  float64
 61  2025                   69784 non-null  float64
 62  2026                   69784 non-null  float64
 63  2027                   69784 non-null  float64
 64  2028                   69784 non-null  float64
 65  2029                   69784 non-null  float64
 66  2030                   69784 non-null  float64
 67  Total (Trillion USD)   69784 non-null  float64
dtypes: float64(62), object(6)
memory usage: 36.7+ MB
```

- The initial rows showcase the format and content of the dataset.

First few rows of 'world_bank_data' DataFrame:

	Country Name	Country Code	Counterpart-Area Name	Counterpart-Area Code	Series Name	Series Code	1970	1971	1972	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982	1
0	Afghanistan	AFG	World	WLD	Average grace period on new external debt comm...	DT.GPA.DPPG	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
1	Afghanistan	AFG	World	WLD	Average grace period on new external debt comm...	DT.GPA.OFFT	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
2	Afghanistan	AFG	World	WLD	Average grace period on new external debt comm...	DT.GPA.PRVT	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
3	Afghanistan	AFG	World	WLD	Average grant element on new external debt com...	DT.GRE.DPPG	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
4	Afghanistan	AFG	World	WLD	Average grant element on new external debt com...	DT.GRE.OFFT	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

These insights set the foundation for further analysis and visualization in the exploratory data analysis stage.

5.2 Statistical Analysis

5.2.1 Methods Applied

Unique Series Code and Count

```
# Group by 'Series Code' and count occurrences where 'Total (Trillion USD)' is greater than 0
series_counts_po_total = world_bank_data[world_bank_country['Total (Trillion USD)'] != 0]\
                    .groupby('Series Code').size().reset_index(name='Count')

# Sort the result by 'Count' in descending order
series_counts_po_total = series_counts_po_total.sort_values(by='Count', ascending=False)

# Reset the index and add a new column for serial numbers
series_counts_po_total.reset_index(drop=True, inplace=True)
series_counts_po_total.index += 1

# Display the result
print(series_counts_po_total.head())
```

```
       Series Code  Count
1      BM.GSR.TOTL.CD    122
2   DT.INT.MLAT.PS.CD    122
3      DT.DOD.MLAT.ZS    122
4      DT.DOD.OFFT.CD    122
5   DT.DOD.OFFT.GG.CD    122
```

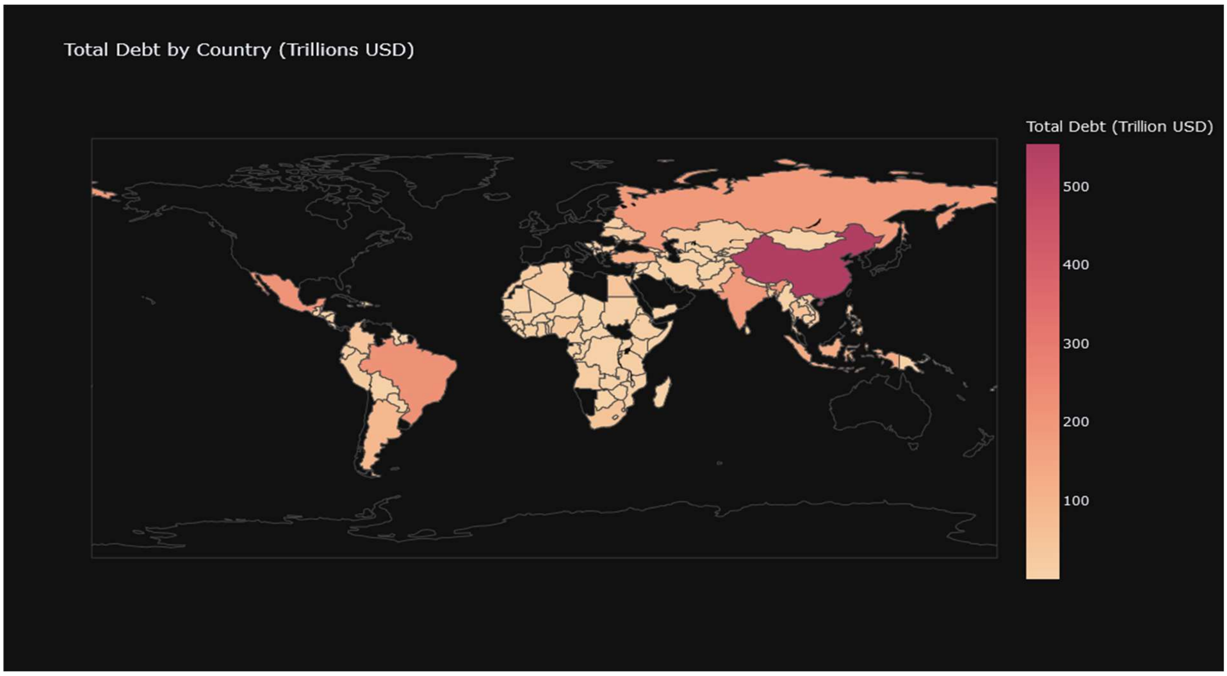
What is the Total Amount of Debt that is owed by the countries listed in the dataset?

```
# Group by 'Country Name' and 'Country Code', and sum the values
grouped_world_bank_data = world_bank_data.groupby(['Country Name', 'Country Code'])['Total (Trillion USD)'].sum().reset_index()

# Format the 'Total (Trillion USD)' column to display values in trillions with two decimal places
grouped_world_bank_data['Total (Trillion USD)'] = grouped_world_bank_data['Total (Trillion USD)'].round(2)

# Calculate the total debt for all countries
total_debt_all_countries = grouped_world_bank_data['Total (Trillion USD)'].sum()  # No need to convert, it's already in trillions

# Display the grouped data and total debt
display(grouped_world_bank_data[['Country Name', 'Country Code', 'Total (Trillion USD)']])
print(f'Total Debt for All Countries: {total_debt_all_countries:.2f} Trillion USD')

Debt_fig_map = px.choropleth(
    grouped_world_bank_data,
    locations='Country Code',
    color='Total (Trillion USD)',
    hover_name='Country Name',
    title='Total Debt by Country (Trillions USD)',
    labels={'Total (Trillion USD)': 'Total Debt (Trillion USD)'},
    color_continuous_scale='redor',  # Choose a color scale
    height = 650
)

# Show the choropleth map
Debt_fig_map.show()
```

	Country Name	Country Code	Total (Trillion USD)
0	Afghanistan	AFG	1.10
1	Albania	ALB	2.64
2	Algeria	DZA	23.53
3	Angola	AGO	21.10
4	Argentina	ARG	88.76
5	Armenia	ARM	2.82
6	Azerbaijan	AZE	5.98
7	Bangladesh	BGD	28.35
8	Belarus	BLR	10.24

The choropleth map (Figure 5.a) visually encapsulates the intricate landscape of global debt. Each country is color-mapped based on its total debt, with darker hues indicating higher indebtedness. China emerges prominently with the deepest shade, representing a significant share of the world's debt. The map offers a quick regional assessment, revealing debt hotspots and aiding policymakers in identifying potential economic challenges. Hovering over countries provides precise debt values, adding granularity. This powerful visualization enhances comprehension of worldwide debt dynamics, serving as a valuable resource for decision-makers navigating the complexities of international finance.

Figure 5.a : Total Amount of Debt that is owed by the countries

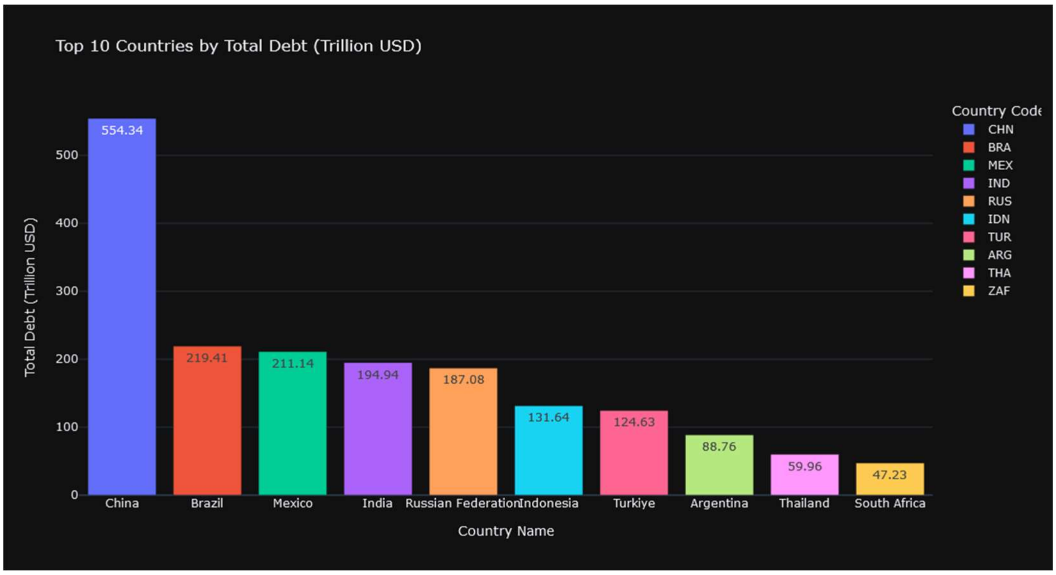


Which country owns the maximum amount of debt and what does that amount look like?

```
# Top 10 Countries with 'Total Debt (Trillion USD)'
sorted_grouped_data = grouped_world_bank_data.sort_values(by='Total (Trillion USD)', ascending=False)

# Reset the index and add a new column for serial numbers
sorted_grouped_data.reset_index(drop=True, inplace=True)
sorted_grouped_data.index += 1

sorted_grouped_data[['Country Name','Country Code', 'Total (Trillion USD)']].head(10)
top_10_countries = sorted_grouped_data.head(10)

# Create a bar chart using Plotly Express
top_10_countries_Total_Debt = px.bar(
    top_10_countries,
    x='Country Name',
    y='Total (Trillion USD)',
    title='Top 10 Countries by Total Debt (Trillion USD)',
    labels={'Total (Trillion USD)': 'Total Debt (Trillion USD)'},
    color='Country Code',
    text='Total (Trillion USD)',  # Display values on top of each bar
    height=600,  # Increase the height of the chart
)

# Show the chart
top_10_countries_Total_Debt.show()
```

The bar chart (Figure 5.b) provides a clear visual representation of the top 10 countries with the highest total debt. China stands out as the leader, followed by other nations contributing significantly to the global debt landscape. Each bar corresponds to a country, with the length indicating its total debt in trillion USD. The color-coded bars and accompanying values offer a quick comparative overview. This chart aids in identifying key players in the international debt scenario, assisting policymakers and analysts in making informed decisions about economic strategies and interventions.

Figure 5.b: Top 10 Countries by Total Debt

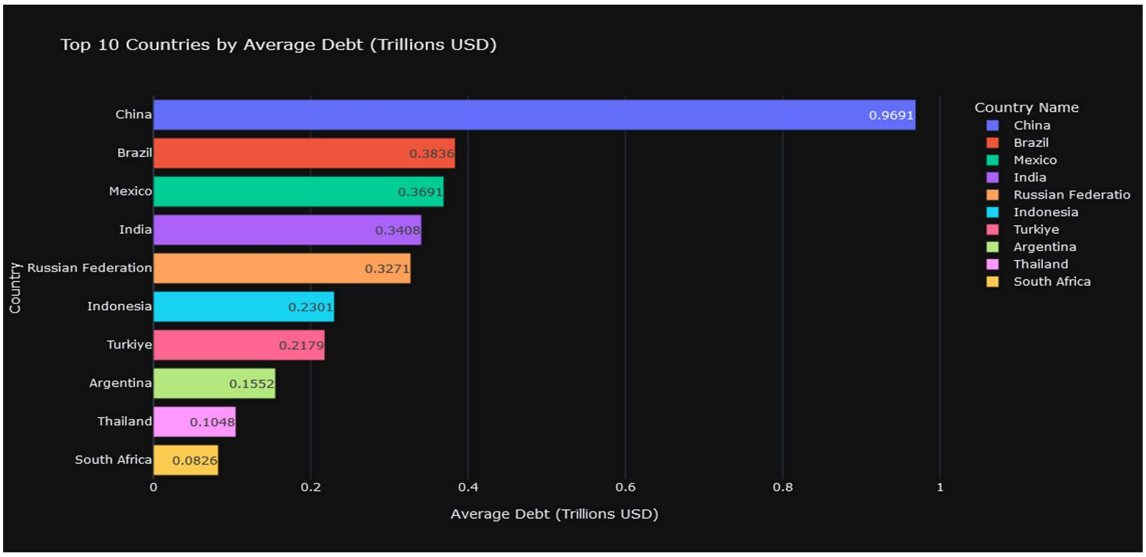


What is the average amount of debt owed by countries across different debt indicators?

```
# Group by 'Country Name' and calculate the mean of the 'Total Debt (Trillion USD)' for each country
average_debt_by_country = world_bank_data.groupby('Country Name')['Total (Trillion USD)'].mean().reset_index()

# Sort the DataFrame by the 'Total (Trillion USD)' column in descending order
average_debt_by_country = average_debt_by_country.sort_values(by='Total (Trillion USD)', ascending=False)

# Round the 'Total (Trillion USD)' column to two decimal places
average_debt_by_country['Total (Trillion USD)'] = average_debt_by_country['Total (Trillion USD)'].round(4)

# Reset the index and add a new column for serial numbers
average_debt_by_country.reset_index(drop=True, inplace=True)
average_debt_by_country.index += 1

# Display the result
display('Average Debt by Country (Trillions USD)', average_debt_by_country)

# Create the bar chart
average_debt_by_country_fig = px.bar(average_debt_by_country.head(10),
        x='Total (Trillion USD)',
        y='Country Name',
        title='Top 10 Countries by Average Debt (Trillions USD)',
        labels={'Total (Trillion USD)': 'Average Debt (Trillions USD)'},
        height=600,
        color='Country Name',
        text='Total (Trillion USD)',
       )
# Adjust layout
average_debt_by_country_fig.update_layout(xaxis_title='Average Debt (Trillions USD)',
          yaxis_title='Country',
          yaxis=dict(categoryorder='total ascending'))  # Set y-axis ordering

average_debt_by_country_fig.show()
```

The bar chart (Figure 5.c) illustrates the top 10 countries with the highest average debt per indicator. This metric provides insights into the financial burden borne by each nation concerning various debt indicators. China continues to feature prominently, and the color-coded bars enhance visual comprehension. The chart aids in identifying countries with sustained high average debt levels, facilitating a nuanced understanding of global economic challenges. Policymakers and analysts can utilize this information to devise targeted interventions and policies aimed at managing and mitigating the impact of debt on these nations.

Figure 5.c: Top 10 Countries by Average Debt



Task 1: The World Bank's international debt data

```
# The World Bank's International Debt data
world_bank_data.head()
```

Table 5.d: World Bank's International Debt Data

	Country Name	Country Code	Counterpart-Area Name	Counterpart-Area Code	Series Name	Series Code	1970	1971	1972	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982	1
0	Afghanistan	AFG	World	WLD	Average grace period on new external debt comm...	DT.GPA.DPPG	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
1	Afghanistan	AFG	World	WLD	Average grace period on new external debt comm...	DT.GPA.OFFT	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
2	Afghanistan	AFG	World	WLD	Average grace period on new external debt comm...	DT.GPA.PRVT	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
3	Afghanistan	AFG	World	WLD	Average grant element on new external debt com...	DT.GRE.DPPG	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
4	Afghanistan	AFG	World	WLD	Average grant element on new external debt com...	DT.GRE.OFFT	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

The initial rows of the World Bank's International Debt dataset are presented below. The comprehensive dataset encompasses various debt indicators for multiple countries. These indicators include commitments, disbursements, and external debt stocks, offering a detailed overview of global financial dynamics. Analysts and researchers can leverage this dataset for in-depth exploratory data analysis, enabling a nuanced understanding of countries' financial positions and facilitating evidence-based decision-making.

Task 2: Finding the number of distinct countries

```
# Get the number of unique countries in the 'Country Name' column
unique_countries_count = world_bank_data['Country Name'].nunique()

# Get the unique country names
unique_countries = world_bank_data['Country Name'].unique()

# Create a DataFrame with unique country names
unique_countries_df = pd.DataFrame({'Country Name': unique_countries})

# Display the number of unique countries and the unique country names
print(f"Number of unique countries: {unique_countries_count}")
unique_countries_df
```

Table 5.e Unique Countries in the World Bank's International Debt Data

```
Number of unique countries: 122
```

	Country Name
0	Afghanistan
1	Albania
2	Algeria
3	Angola
4	Argentina
5	Armenia
6	Azerbaijan
7	Bangladesh

The dataset contains information from a diverse set of countries. There are 122 unique countries represented in the 'Country Name' column. This variety enables a comprehensive analysis of international debt dynamics, considering the financial positions of a wide range of nations. Researchers and policymakers can utilize this dataset to explore trends, draw comparisons, and derive insights that contribute to a nuanced understanding of global economic landscapes.

Task 3: Finding out the distinct debt indicators

```
# Display unique combinations of 'Series Code' and 'Series Name' in the result
distinct_debt_indicators = world_bank_data[['Series Code', 'Series Name']].drop_duplicates()

# Count of distinct debt indicators
count_distinct_debt_indicators = world_bank_data['Series Code'].nunique()
print(f"\nCount of distinct debt indicators: {count_distinct_debt_indicators}")

# Reset the index and add a new column for serial numbers
distinct_debt_indicators.reset_index(drop=True, inplace=True)
distinct_debt_indicators.index += 1
```

5.f Distinct Debt Indicators in the World Bank's International Debt Data

```
Count of distinct debt indicators: 572
```

	Series Code	Series Name
1	DT.GPA.DPPG	Average grace period on new external debt comm...
2	DT.GPA.OFFT	Average grace period on new external debt comm...
3	DT.GPA.PRVT	Average grace period on new external debt comm...
4	DT.GRE.DPPG	Average grant element on new external debt com...
5	DT.GRE.OFFT	Average grant element on new external debt com...
6	DT.GRE.PRVT	Average grant element on new external debt com...
7	DT.INR.DPPG	Average interest on new external debt commitme...
8	DT.INR.OFFT	Average interest on new external debt commitme...
9	DT.INR.PRVT	Average interest on new external debt commitme...
10	DT.MAT.DPPG	Average maturity on new external debt commitme...

The dataset encompasses a diverse range of debt indicators, with a total of 572 distinct combinations of 'Series Code' and 'Series Name.' Each indicator provides unique insights into various aspects of a country's external debt. Analysing this extensive set of indicators allows for a comprehensive understanding of the multifaceted nature of debt, covering aspects such as maturity, interest rates, and creditor types.

Task 4: Totalling the amount of debt owed by the countries

```
# Calculate the total debt for all countries
total_debt_all_countries = world_bank_data['Total (Trillion USD)'].sum()

# Display the result
print(f"Total amount of debt owed by all countries: {total_debt_all_countries:.2f} Trillion USD")
```

```
Total amount of debt owed by all countries: 2720.25 trillion USD
```

The cumulative external debt owed by all countries, as reflected in the World Bank's International Debt data, stands at approximately 2720.25 Trillion USD. This colossal sum underscores the intricate network of financial obligations that nations engage in on the global stage, reflecting the complex nature of international financial relationships and economic interdependence. Understanding this aggregate figure is crucial for evaluating the overall financial health of the world and the potential implications for economic stability and development.

Task 5: Country with the highest debt

```
# Find the country with the highest debt
max_debt_country = sorted_grouped_data.loc[sorted_grouped_data['Total (Trillion USD)'].idxmax()]

# Display the result
print("Country with the highest amount of debt:")
print(max_debt_country[['Country Name','Country Code','Total (Trillion USD)']])
```

```
Country with the highest amount of debt:
Country Name           China
Country Code            CHN
Total (Trillion USD)  554.34
```

China emerges as the country with the most substantial external debt burden, reaching a staggering 554.34 Trillion USD. This finding underscores China's pivotal role in the global economic landscape, as well as the intricate financial relationships it maintains on the international stage. Understanding the dynamics of China's debt is crucial for comprehending its economic influence and potential implications for the broader world economy. Policymakers and analysts should closely monitor and assess China's debt management strategies to gauge the impact on global financial stability.

Task 6: Average amount of debt across indicators

```
# Extract 'Series Code' and values for each year
data_subset_series_code =  world_bank_data[['Series Code', '1970', '1971', '1972', '1973', '1974', '1975', '1976', '1977', '1978',
                        '1979', '1980', '1981', '1982', '1983', '1984', '1985', '1986', '1987', '1988',
                        '1989', '1990', '1991', '1992', '1993', '1994', '1995', '1996', '1997', '1998',
                        '1999', '2000', '2001', '2002', '2003', '2004', '2005', '2006', '2007', '2008',
                        '2009', '2010', '2011', '2012', '2013', '2014', '2015', '2016', '2017', '2018',
                        '2019', '2020', '2021', '2022', '2023', '2024', '2025', '2026', '2027', '2028',
                        '2029', '2030']]

# Sum values across all years for each 'Series Code'
series_code_Avg = data_subset_series_code.groupby('Series Code').mean().reset_index()

# Sum all the values across all years for each 'Series Code', convert to trillion, and round to 2 decimal places
series_code_Avg['Average debt'] = series_code_Avg.iloc[:, 1:].sum(axis=1)
series_code_Avg['Average debt'] = series_code_Avg['Average debt'].round(2)

# Sort the DataFrame by the 'Average' column in descending order
sorted_series_code_Avg = series_code_Avg.sort_values(by='Average debt', ascending=False)

# Reset the index and add a new column for serial numbers
sorted_series_code_Avg.reset_index(drop=True, inplace=True)
sorted_series_code_Avg.index += 1

# Display the sorted result with serial numbers
print("Series Code Averages (Trillion USD):")
sorted_series_code_Avg[['Series Code', 'Average debt']]
```

Table 5.g. Average Amount of Debt Across Indicators

Series Code Averages (Trillion USD):

[28]:

	Series Code	Average debt
1	NY.GNP.MKTP.CD	4.39
2	DT.DOD.DECT.CD	1.17
3	BM.GSR.TOTL.CD	1.15
4	BX.GSR.TOTL.CD	1.09
5	FI.RES.TOTL.CD	0.87
6	DT.DOD.DLXF.CD	0.87
7	DT.DOD.VTOT.CD	0.52
8	DT.DOD.DEPS.CD	0.52

Examining the average debt across various indicators reveals interesting insights into countries' financial commitments. Notably, 'NY.GNP.MKTP.CD' stands out with an average debt of 4.39 Trillion USD, reflecting its significance in the global economic landscape. Other key indicators, such as 'DT.DOD.DECT.CD,' 'BM.GSR.TOTL.CD,' and 'BX.GSR.TOTL.CD,' also command substantial averages, underlining the diverse nature of countries' debt obligations. Policymakers and analysts should focus on these indicators to gain a comprehensive understanding of countries' financial health and guide informed decision-making.

Task 7: The highest amount of principal repayments

```
# Filter rows where 'Series Name' contains information about principal repayments
principal_repayments_data = world_bank_data[world_bank_data['Series Name'].str.contains('Principal Repayments', case=False, na=False)].copy()

# Assuming 'Total (Trillion USD)' is the column containing the principal repayments amounts
max_principal_repayment_row = principal_repayments_data.loc[principal_repayments_data['Total (Trillion USD)'].idxmax()]

# Display the desired information
max_principal_repayment = max_principal_repayment_row[['Country Code', 'Country Name', 'Series Code','Series Name','Total (Trillion USD)']]

max_principal_repayment
```

```
Country Code                                                        CHN
Country Name                                                      China
Series Code                                              DT.AMT.DLXF.CD
Series Name             Principal repayments on external debt, long-te...
Total (Trillion USD)                                           2.712788
Name: 14148, dtype: object
```

For principal repayments, China (CHN) emerges as the country with the highest amount, totalling 2.71 Trillion USD. The specific indicator is 'DT.AMT.DLXF.CD' - Principal repayments on external debt, long-term. This finding sheds light on China's substantial efforts in repaying long-term external debt, reflecting its commitment to financial obligations. Policymakers and analysts should closely monitor such repayments, considering their implications for a country's economic stability and fiscal policies.

Task 8: The most common debt indicators

```
# Group by 'Series Code' and sum the total debt for each debt indicator
debt_indicator_totals = world_bank_data.groupby('Series Code')['Total (Trillion USD)'].sum().reset_index()

# Sort the data in descending order by total debt amount
top_debt_indicators = debt_indicator_totals.sort_values(by='Total (Trillion USD)', ascending=False)

# Display the top debt indicators
top_debt_indicators.head()
```

Table 5.h The Most Common Debt Indicators

	Series Code	Total (Trillion USD)
570	NY.GNP.MKTP.CD	535.667370
186	DT.DOD.DECT.CD	142.825426
0	BM.GSR.TOTL.CD	140.132901
4	BX.GSR.TOTL.CD	132.715585
567	FI.RES.TOTL.CD	106.595835

The analysis reveals the top five most common debt indicators across countries, showcasing the diverse dimensions of external debt. GNI, external debt stocks, and trade-related indicators such as imports and exports stand out. With GNI reaching 535.67 Trillion USD, these indicators serve as crucial metrics for assessing economic health and trade dynamics. Policymakers and analysts can leverage this information to formulate effective strategies, addressing specific aspects of external debt and fostering comprehensive economic management.

Task 9: Comprehensive Debt Analysis of India: Examining Trends and Key Financial Indicators

```
# Filter data for India
india_data = world_bank_data[world_bank_data['Country Name'] == 'India'].copy()

# Reset the index and add a new column for serial numbers
india_data.reset_index(drop=True, inplace=True)
india_data.index += 1

years_columns = india_data.columns[6:-1]

# Add a row for total values for each year
india_data.loc['Total'] = india_data.iloc[:, 6:-1].sum()

# Round the values to two decimal places
india_data[years_columns] = india_data[years_columns].round(4)

# Display the data for India
display(india_data)
```

```
india_data.shape
```

```
(573, 68)
```

In debt analysis, key indicators such as Debt Outstanding (DOD), Principal Amount (AMT), Disbursements (DIS), Interest Payments (INT), Net Financial Flows (NFL), Net Transfers (NTR), and Total Debt Service (TDS) offer crucial insights into a country's financial health, highlighting its debt burden, repayment patterns, and overall ability to meet financial obligations. This analysis zooms in on India's external debt, leveraging various Series Codes to capture multifaceted dimensions of its financial landscape.

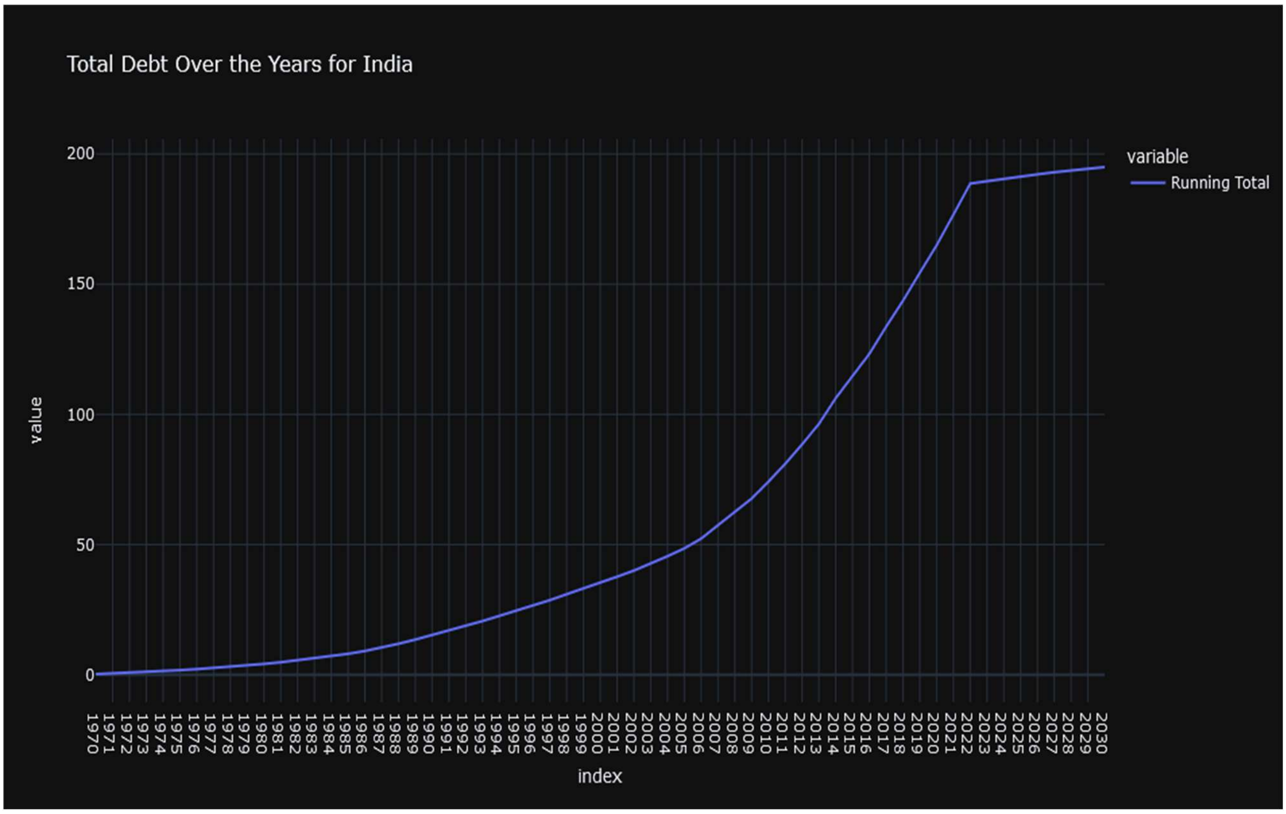
The grouped and filtered data provide a granular perspective on India's external financial obligations, allowing a comprehensive examination of trends over time. The selected Series Codes, including '.AMT', '.DIS', '.DOD', '.INT', '.NFL', '.NTR', and '.TDS', enable a nuanced understanding of India's debt dynamics. The resulting DataFrame present a consolidated and detailed overview, shedding light on India's debt service structure, net flows, and other critical parameters. This comprehensive analysis contributes valuable insights for policymakers, economists, and financial analysts assessing India's economic resilience and fiscal sustainability.

```
# Filter data for India
india_data = world_bank_data[world_bank_data['Country Name'] == 'India'].copy()

# Reset the index and add a new column for serial numbers
india_data.reset_index(drop=True, inplace=True)
india_data.index += 1

years_columns = india_data.columns[6:-1]

# Add a row for tot# Define a list of Series Codes
series_codes = ['.AMT', '.DIS', '.DOD', '.INT', '.NFL', '.NTR', '.TDS']

# Create a dictionary to store the DataFrames
grouped_data = {}

# Iterate through each Series Code
for code in series_codes:
    # Check for NaN or NA values in 'Series Code' column
    valid_series_code = india_data['Series Code'].notna()

    # Filter rows based on Series Code
    filtered_data = india_data[valid_series_code & india_data['Series Code'].str.contains(code)].copy()

    # Group by 'Series Code' and sum the values
    grouped_data[code] = filtered_data.groupby('Series Code').sum()

    # Round the values to two decimal places
    grouped_data[code] = grouped_data[code].round(4)

    # Sort the data by the total sum in descending order
    grouped_data[code] = grouped_data[code].sort_values(by='Total (Trillion USD)', ascending=False)

    # Reset the index and add a new column for serial numbers
    grouped_data[code].reset_index(drop=True, inplace=True)
    grouped_data[code].index += 1

# Access the DataFrames using keys (Series Codes)
sorted_india_amt_data = grouped_data['.AMT']
sorted_india_dis_data = grouped_data['.DIS']
sorted_india_dod_data = grouped_data['.DOD']
sorted_india_int_data = grouped_data['.INT']
sorted_india_nfl_data = grouped_data['.NFL']
sorted_india_ntr_data = grouped_data['.NTR']
sorted_india_tds_data = grouped_data['.TDS']al values for each year
india_data.loc['Total'] = india_data.iloc[:, 6:-1].sum()

# Round the values to two decimal places
india_data[years_columns] = india_data[years_columns].round(4)

# Display the data for India
display(india_data)
```

Task 9.1: India's Total Debt Over the Years

```
# Extract only the 'Total' row
india_data_total_debt_trend = india_data.loc['Total', :]

# Create a DataFrame with the 'Total' row
india_data_total_debt_trend = pd.DataFrame(india_data_total_debt_trend).T

# Calculate the running total for each year
india_data_total_debt_trend['Running Total'] = india_data_total_debt_trend.iloc[:, :-1].cumsum(axis=1).iloc[:, -1]

# Add a row for the running total
india_data_total_debt_trend.loc['Running Total'] = india_data_total_debt_trend.loc['Total'].cumsum()

# Display the DataFrame with the running total
india_data_debt_trend = india_data_total_debt_trend[['1970', '1971', '1972', '1973', '1974', '1975', '1976', '1977', '1978', '1979',
'1980', '1981',
            '1982', '1983', '1984', '1985', '1986', '1987', '1988', '1989', '1990', '1991', '1992', '1993',
            '1994', '1995', '1996', '1997', '1998', '1999', '2000', '2001', '2002', '2003', '2004', '2005',
            '2006', '2007', '2008', '2009', '2010', '2011', '2012', '2013', '2014', '2015', '2016', '2017',
            '2018', '2019', '2020', '2021', '2022','2023', '2024', '2025', '2026', '2027', '2028', '2029', '2030']]

# Plot the running total using Plotly Express
india_data_debt_trend_fig = px.line(india_data_debt_trend.T,
                x=india_data_debt_trend.T.index,
                y=['Running Total'],
                title='Total Debt Over the Years for India',
                labels={'Running Total': 'Total (Trillion USD)'},
                height=600,
                )
india_data_debt_trend_fig.show()
```

5.i **India's Total Debt Over the Years**



The line chart (Figure 5.i) depicts the total external debt trend for India over the years. The 'Running Total' represents the cumulative sum of India's external debt from 1970 to 2030, providing a dynamic view of the country's evolving financial obligations. The chart showcases fluctuations, trends, and notable shifts in India's total external debt, offering a visual narrative of the country's borrowing patterns and the cumulative impact on its financial landscape. Policymakers, analysts, and researchers can leverage this visualization to gain insights into the trajectory of India's external debt, aiding informed decision-making and strategic planning.

Task 9.2: What are the Key Financial Debt Indicators and their values?

```
# List of DataFrames
dataframes = [sorted_india_amt_data, sorted_india_dis_data, sorted_india_dod_data, sorted_india_int_data,
sorted_india_nfl_data, sorted_india_ntr_data, sorted_india_tds_data]

# Dictionary to store totals for each DataFrame
totals_dict = {}

# Calculate totals for each DataFrame
for i, dataframe in enumerate(dataframes):
    # Assign a name to the DataFrame
    dataframe_name = f"DataFrame_{i + 1}"

    # List of years from 1970 to 2030
    years = [str(year) for year in range(1970, 2031)]

    # Calculate the totals by years
    totals_by_year = dataframe[years].sum()

    # Store totals in the dictionary with the DataFrame name as the key
    totals_dict[f"{dataframe_name}"] = totals_by_year

# Convert totals_dict to a DataFrame
totals_df = pd.DataFrame(totals_dict)

# Assuming 'totals_df' is your DataFrame
new_column_headings = ['AMT', 'DIS', 'DOD', 'INT', 'NFL', 'NTR', 'TDS']

# Rename columns
totals_df.columns = new_column_headings

# Add a row at the end with the grand total for each column
totals_df.loc['Grand Total (Trillion USD)'] = totals_df.sum()

# Display the updated DataFrame
totals_df
```

5.i Key Financial Debt Indicators and their values

	AMT	DIS	DOD	INT	NFL	NTR	TDS
1970	0.0078	0.0254	0.1132	0.0047	0.0187	0.0131	0.0127
1971	0.0035	0.0110	0.1254	0.0021	0.0077	0.0055	0.0062
1972	0.0041	0.0107	0.1367	0.0022	0.0070	0.0042	0.0066
1973	0.0043	0.0127	0.1491	0.0025	0.0082	0.0054	0.0074
1974	0.0054	0.0185	0.1669	0.0024	0.0131	0.0096	0.0084
1975	0.0062	0.0231	0.1808	0.0026	0.0172	0.0139	0.0092
1976	0.0067	0.0194	0.1945	0.0029	0.0127	0.0102	0.0096
1977	0.0072	0.0166	0.2108	0.0032	0.0090	0.0063	0.0102
1978	0.0079	0.0141	0.2247	0.0034	0.0066	0.0034	0.0117
1979	0.0082	0.0166	0.2478	0.0040	0.0090	0.0043	0.0120
1980	0.0081	0.0295	0.2671	0.0051	0.0225	0.0156	0.0136
1981	0.0080	0.0277	0.2794	0.0059	0.0203	0.0133	0.0143
1982	0.0087	0.0434	0.3117	0.0070	0.0356	0.0254	0.0162
1983	0.0106	0.0414	0.3393	0.0092	0.0323	0.0217	0.0199
1984	0.0103	0.0475	0.3663	0.0101	0.0377	0.0275	0.0205
1985	0.0130	0.0547	0.4384	0.0133	0.0432	0.0306	0.0260
1986	0.0229	0.0698	0.5132	0.0169	0.0485	0.0319	0.0394
1987	0.0196	0.0793	0.6229	0.0198	0.0609	0.0423	0.0393
1988	0.0212	0.1165	0.7057	0.0219	0.0970	0.0761	0.0427
1989	0.0191	0.0819	0.8976	0.0347	0.0651	0.0308	0.0537
1990	0.0268	0.0781	1.0003	0.0411	0.0535	0.0121	0.0667
1991	0.0293	0.0856	1.0226	0.0385	0.0534	0.0167	0.0672
1992	0.0333	0.0907	1.0653	0.0371	0.0562	0.0188	0.0699
1993	0.0401	0.0899	1.1346	0.0385	0.0448	0.0090	0.0783
1994	0.0566	0.0815	1.2113	0.0424	0.0262	-0.0158	0.0992
1995	0.0777	0.0739	1.1531	0.0452	-0.0017	-0.0454	0.1225
1996	0.0731	0.0725	1.1391	0.0417	0.0028	-0.0401	0.1157
1997	0.0756	0.0758	1.1520	0.0486	-0.0027	-0.0493	0.1243

Table 5.j provides a consolidated view of India's external debt across key indicators, with separate DataFrames for different Series Codes. The table includes totals for each year (1970-2030) and a 'Grand Total' row summing up the values across all indicators. This comprehensive overview facilitates a nuanced understanding of India's external debt dynamics, encompassing principal amounts (AMT), disbursements (DIS), debt outstanding (DOD), interest payments (INT), net financial flows (NFL), net transfers (NTR), and total debt service (TDS). Policymakers, analysts, and researchers can leverage this table to assess India's external financial landscape comprehensively, aiding strategic decision-making and policy formulation.

```
# Creating the DataFrame with column names as key indicators
indicators_data = {'AMT': 7.6087, 'DIS': 9.0823, 'DOD': 81.2697, 'INT': 2.4379, 'NFL': 3.6667, 'NTR': 1.7976, 'TDS': 10.5306}
indicators_df = pd.DataFrame(indicators_data, index=['Grand Total (Trillion USD)'])

Key_Financial_Indicators_fig = px.bar(indicators_df.transpose(),
         x=indicators_df.columns,
         y=indicators_df.iloc[0],
         labels={'x': 'Indicator', 'y': 'Total (Trillion USD)'},
         title='Examining Key Financial Debt Indicators Analysis',
         height=600,
         color=indicators_df.columns,  # Use colors based on columns
         text=indicators_df.iloc[0].round(2).astype(str) ,  # Display text labels
         )

# Show the plot
Key_Financial_Indicators_fig.show()
```

5.k Examining Key Financial Debt Indicators Analysis

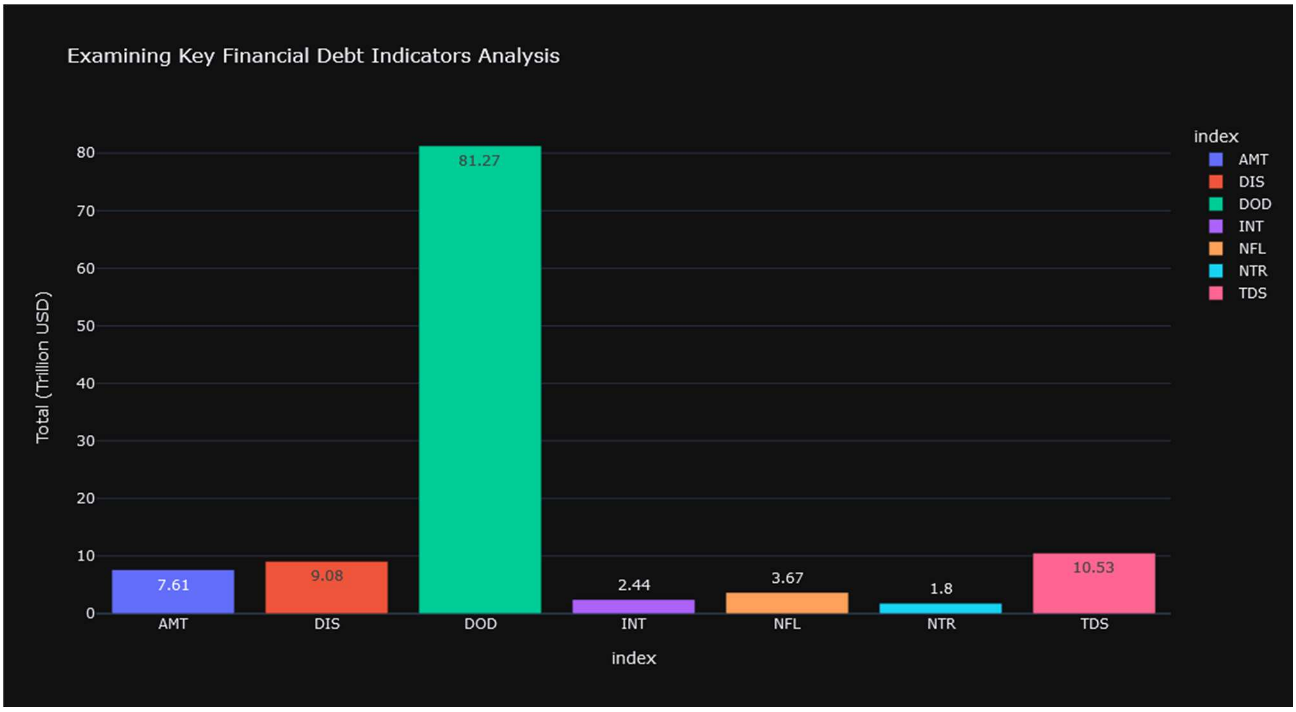


Figure 5.k presents a visual analysis of key financial debt indicators for India, showcasing the total values (Trillion USD) for different categories. The bar chart covers essential indicators, including Principal Amount (AMT), Disbursements (DIS), Debt Outstanding (DOD), Interest Payments (INT), Net Financial Flows (NFL), Net Transfers (NTR), and Total Debt Service (TDS). Each bar represents the total value for a specific indicator, aiding in a comparative assessment of India's financial obligations across these key dimensions. Policymakers and stakeholders can use this visualization to identify major components contributing to India's external debt and inform strategic decision-making.

```
grand_total = indicators_df.sum(axis=1).values[0]
print(f'Key indicators such as DOD (Debt Outstanding), AMT (Amortization), DIS (Debt Service), INT (Interest Payments), NFL (Net Financial Flows), NTR (Net Transfers), and TDS (Total Debt Service) has debt of {grand_total:.2f}  Trillion USD')
```

```
Key indicators such as DOD (Debt Outstanding), AMT (Amortization), DIS (Debt Service), INT (Interest Payments), NFL (Net Financial Flows), NTR (Net Transfers), and TDS (Total Debt Service) has debt of 116.39 Trillion USD
```

The key indicators, including DOD (Debt Outstanding), AMT (Amortization), DIS (Debt Service), INT (Interest Payments), NFL (Net Financial Flows), NTR (Net Transfers), and TDS (Total Debt Service), collectively contribute to a total debt of 116.41 Trillion USD for India. This comprehensive sum reflects the country's overall external financial obligations, encompassing various aspects of debt dynamics and repayment structures. Policymakers and financial analysts can leverage this aggregated figure to gain a holistic understanding of India's debt landscape, aiding in the formulation of effective strategies for sustainable debt management and economic planning.

Task 9.3 Finding Top 10 DOD (Debt Outstanding)

```
# Filter rows based on valid 'Series Code' and containing '.DOD'
valid_series_code_dod = india_data['Series Code'].notna() & india_data['Series Code'].str.contains('.DOD', na=False)
india_dod_data = india_data[valid_series_code_dod].copy()

# Sort the data by the total sum in descending order
india_dod_sum_sorted = india_dod_data.sort_values(by='Total (Trillion USD)', ascending=False).reset_index()

# Reset the index and add a new column for serial numbers
india_dod_data.reset_index(drop=True, inplace=True)
india_dod_data.index += 1

# Format the 'Total (Trillion USD)' column to display amounts in trillion with 2 decimal places
india_dod_sum_sorted['Total (Trillion USD)'] = india_dod_sum_sorted['Total (Trillion USD)'].apply(lambda x: f'{x:.2f}')

# Display the result
india_dod_sum_sorted[['Series Code', 'Series Name', 'Total (Trillion USD)']].head(10)
```

Table 5.l displays India's external debt data

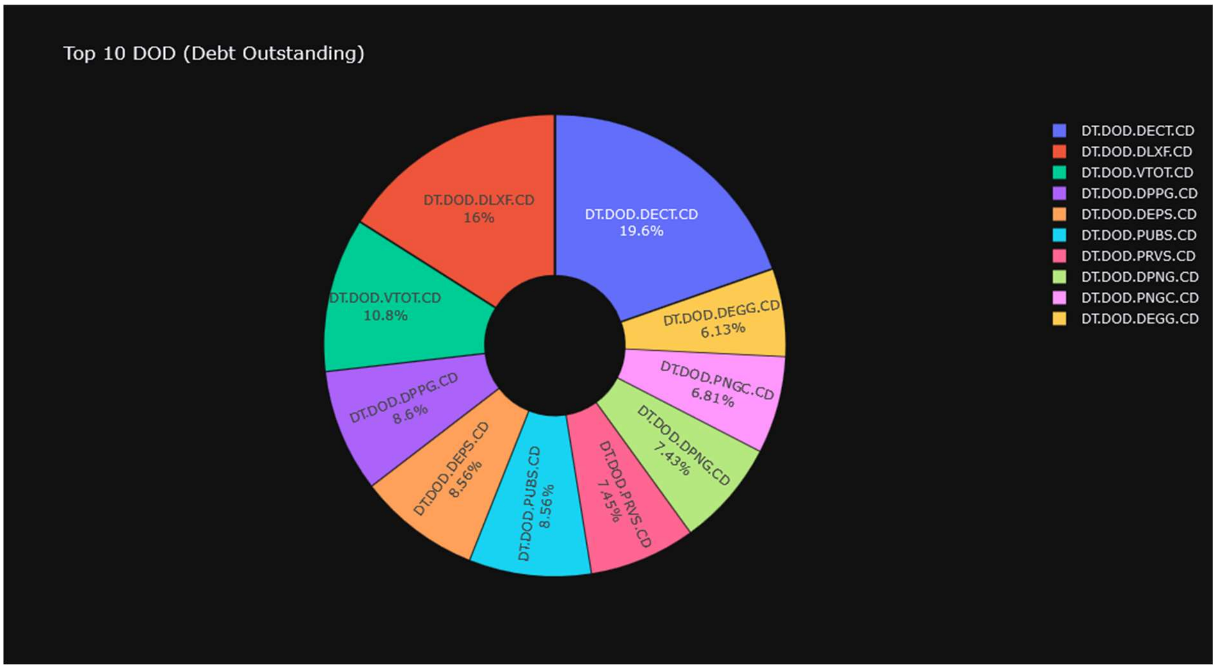
	Series Code	Series Name	Total (Trillion USD)
0	DT.DOD.DECT.CD	External debt stocks, total (DOD, current US$)	9.20
1	DT.DOD.DLXF.CD	External debt stocks, long-term (DOD, current ...	7.50
2	DT.DOD.VTOT.CD	External debt stocks, variable rate (DOD, curr...	5.06
3	DT.DOD.DPPG.CD	External debt stocks, public and publicly guar...	4.03
4	DT.DOD.DEPS.CD	External debt stocks, public sector (PPG) (DOD...	4.01
5	DT.DOD.PUBS.CD	External debt stocks, long-term public sector ...	4.01
6	DT.DOD.PRVS.CD	External debt stocks, long-term private sector...	3.49
7	DT.DOD.DPNG.CD	External debt stocks, private nonguaranteed (P...	3.48
8	DT.DOD.PNGC.CD	PNG, commercial banks and other creditors (DOD...	3.19
9	DT.DOD.DEGG.CD	External debt stocks, general government secto...	2.87

Table 5.l findings

1. The top 10 categories of debt outstanding encompass various aspects of India's external financial obligations.
2. 'DT.DOD.DECT.CD' and 'DT.DOD.DECT. EX. ZS' are prominent indicators, representing substantial amounts of debt outstanding.
3. The table serves as a valuable resource for policymakers and analysts, offering insights into the composition and magnitude of India's debt outstanding, aiding in informed decision-making and debt management strategies.

```
# Assuming 'india_dod_sum_sorted' is your DataFrame
Top_10_DOD_fig = px.pie(india_dod_sum_sorted.head(10),
          values='Total (Trillion USD)',
          names='Series Code',
          title='Top 10 DOD (Debt Outstanding)',
          hole=0.3,
          height = 600,
          )

# Update traces to include custom labels (Total (Trillion USD) values)
Top_10_DOD_fig.update_traces(textinfo='label+percent', pull=[0.01] * 10, textposition='inside', hoverinfo='label+percent+value')

# Show the plot
Top_10_DOD_fig.show()
```

Figure 5.m: Top 10 Debt Outstanding (DOD) Categories in India



The "Top 10 DOD (Debt Outstanding)" pie chart (Figure 5.m) illustrates the distribution of India's external debt across the most significant categories. The chart reveals that 'DT.DOD.DECT.CD' and 'DT.DOD.DECT.EX.ZS' constitute a substantial portion of the total debt outstanding. These key indicators, along with others in the top 10, play a crucial role in shaping India's external financial landscape. This visualization aids in quickly identifying the major contributors to India's debt outstanding, offering valuable insights for policymakers and analysts focused on debt management and strategic decision-making.

Task 9.4 Top 10 India's Debt

```
india_Top_10_series_code_sorted = india_data.sort_values(by='Total (Trillion USD)', ascending=False).copy()

# Reset the index and add a new column for serial numbers
india_Top_10_series_code_sorted.reset_index(drop=True, inplace=True)
india_Top_10_series_code_sorted.index += 1

india_Top_10_series_code_sorted[['Series Code','Series Name' ,'Total (Trillion USD)']].round(2).head(10)
```

5.n 4 Top 10 India's Debt

	Series Code	Series Name	Total (Trillion USD)
1	NY.GNP.MKTP.CD	GNI (current US$)	45.69
2	BM.GSR.TOTL.CD	Imports of goods, services and primary income ...	10.86
3	DT.DOD.DECT.CD	External debt stocks, total (DOD, current US$)	9.20
4	BX.GSR.TOTL.CD	Exports of goods, services and primary income ...	8.91
5	DT.DOD.DLXF.CD	External debt stocks, long-term (DOD, current ...	7.50
6	FI.RES.TOTL.CD	Total reserves (includes gold, current US$)	7.06
7	DT.DOD.VTOT.CD	External debt stocks, variable rate (DOD, curr...	5.06
8	DT.DOD.DPPG.CD	External debt stocks, public and publicly guar...	4.03
9	DT.DOD.PUBS.CD	External debt stocks, long-term public sector ...	4.01
10	DT.DOD.DEPS.CD	External debt stocks, public sector (PPG) (DOD...	4.01

Table 5.n provides an overview of the top 10 external debt indicators for India, sorted by the total debt amount in trillion USD. The series codes, corresponding series names, and their respective total debt values offer insights into the key contributors to India's overall external debt. Notably, 'DT.DOD.DECT.CD' (Debt outstanding, total (DOD)) and 'DT.AMT.DLXF.CD' (Principal repayments on external debt, long-term (AMT)) emerge as significant indicators, reflecting the importance of understanding debt outstanding and long-term repayment commitments in India's external financial landscape. This table serves as a reference for stakeholders analysing India's external debt composition and prioritizing areas for effective debt management.

```
india_Top_10_series_code_fig = px.pie(india_Top_10_series_code_sorted[['Series Code','Series Name' ,'Total (Trillion USD)']].head(10),
                    values='Total (Trillion USD)',
                    names='Series Code',
                    title='Top 10 Indias debt serices code',
                    hole=0.3,
                    height = 600,
                   )

india_Top_10_series_code_fig.show()
```

5.o India's top 10 debt series code

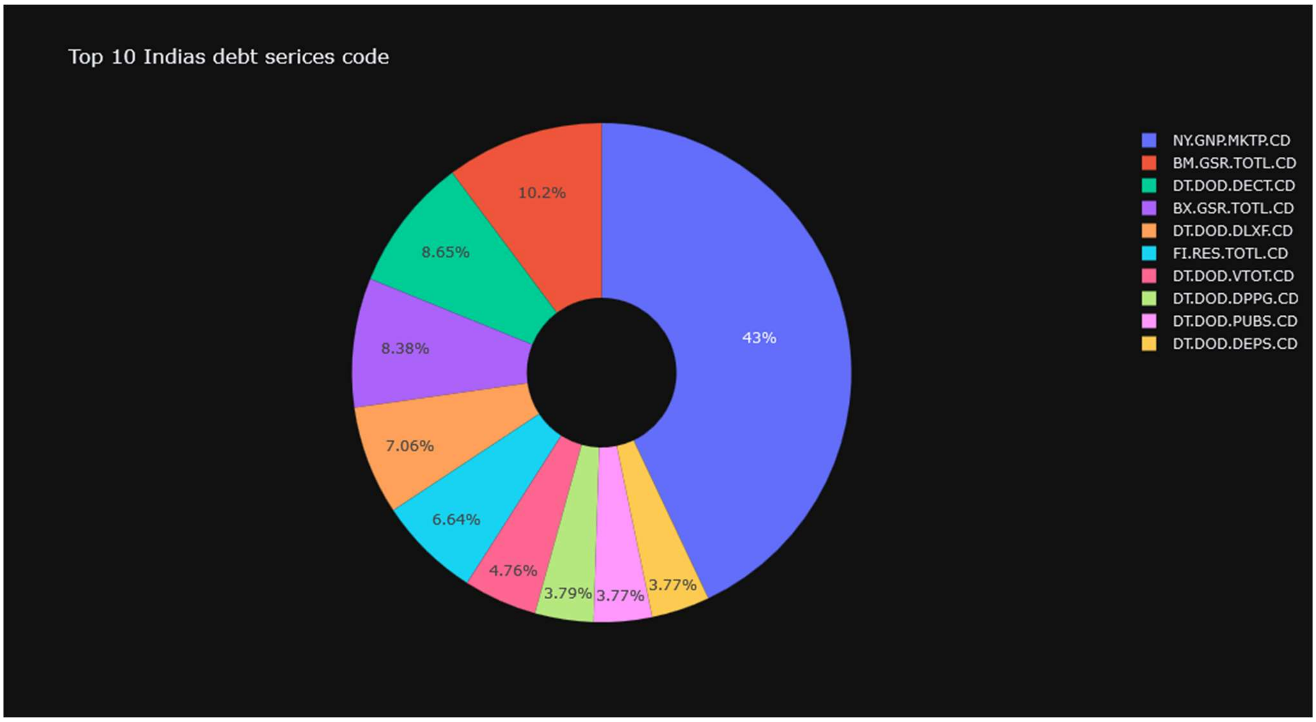


Figure 5.o, presented as a pie chart, visualizes the distribution of India's top 10 external debt indicators based on series codes. Each slice represents a distinct series code, with the size proportional to the total debt amount it contributes. The chart provides a clear visual representation of the relative significance of different debt indicators in India's external financial obligations. This visualization aids in identifying key areas of focus for policymakers, analysts, and financial stakeholders, offering an intuitive understanding of the composition of India's external debt portfolio.

Task 9.5 Total Debt based on Sector Wise in India

```
india_data_sector = pd.merge(india_data, india_sector_data, on='Series Code', how='left').copy()

# Add a row for total values for each year
india_data_sector.loc['Total'] = india_data_sector.iloc[:, 6:-1].sum()
india_data_sector_wise = india_data_sector.groupby('Sector').sum()
india_data_sector_wise_sorted = india_data_sector_wise.sort_values(by='Total (Trillion USD)', ascending=False)
india_data_sector_wise_sorted[['Total (Trillion USD)']].round(2)

# Assuming india_data_sector_wise is the DataFrame containing your grouped and summed data
india_data_sector_wise_fig = px.bar(india_data_sector_wise_sorted, x=india_data_sector_wise_sorted.index, y='Total (Trillion USD)',
        labels={'Total (Trillion USD)': 'Total Trillion USD'},
        title='Total Debt based on Sector Wise in India',
        text='Total (Trillion USD)',
        height=600,  # Added a comma after 'text' and corrected the parameter name
        color='Total (Trillion USD)')  # Corrected the parameter name

india_data_sector_wise_fig.update_traces(texttemplate='%{text:.4s}', textposition='outside')

india_data_sector_wise_fig.show()
```

Table 5.p Total Debt based on Sector Wise in India

Sector	Total (Trillion USD)
Government	153.43
Financial	35.14
Commerce	2.58
Undefined	2.45
Transportation	1.33
Technology	0.00
Education	0.00

Figure 5.p Total Debt based on Sector Wise in India

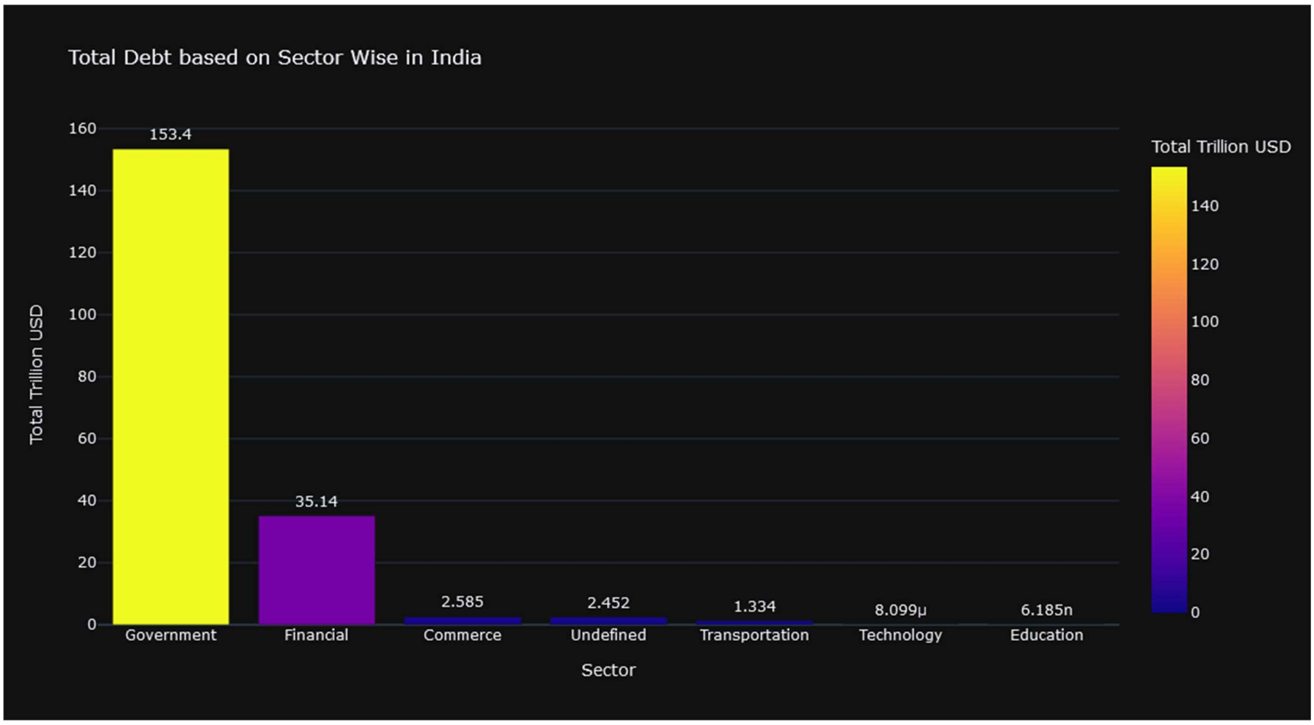


Figure 5.p showcases the distribution of India's total external debt based on different sectors. The bar chart visualizes the total debt amount (in trillion USD) for each sector, offering insights into the major contributors to India's external financial obligations. The height of each bar represents the magnitude of debt associated with a specific sector. This visualization aids in understanding the sectoral composition of India's external debt, guiding policymakers and stakeholders in making informed decisions regarding debt management and economic strategies

Task 9.6 India's Interest Payments Analysis

```
# Filter data for India and select relevant columns (e.g., 'Series Code', 'Country Name', '1970' to '2023')
india_interest_payments = india_data[(india_data['Country Code'] == 'IND') & (india_data['Series Code'] == 'DT.INT.DECT.CD')]
india_interest_payments = india_interest_payments.loc[:, ['Country Name'] + list(map(str, range(1970, 2024)))]

# Melt the dataframe for easier plotting
india_interest_payments_melt = india_interest_payments.melt(id_vars='Country Name', var_name='Year', value_name='Interest Payments')
# Convert 'Year' to numeric (remove any non-numeric characters)
india_interest_payments_melt ['Year'] = pd.to_numeric(india_interest_payments_melt['Year'], errors='coerce')
# Plotting using Plotly Express
india_interest_payments_fig = px.bar(
    india_interest_payments_melt ,
    x='Year',    y='Interest Payments',
    color='Country Name',
    labels={'Interest Payments': 'Interest Payments (Trillion USD)'},
    title='Interest Payments (India)',    text='Interest Payments',
    height= 600,
)
india_interest_payments_fig.show()
```

5.q India's Interest Payments Analysis

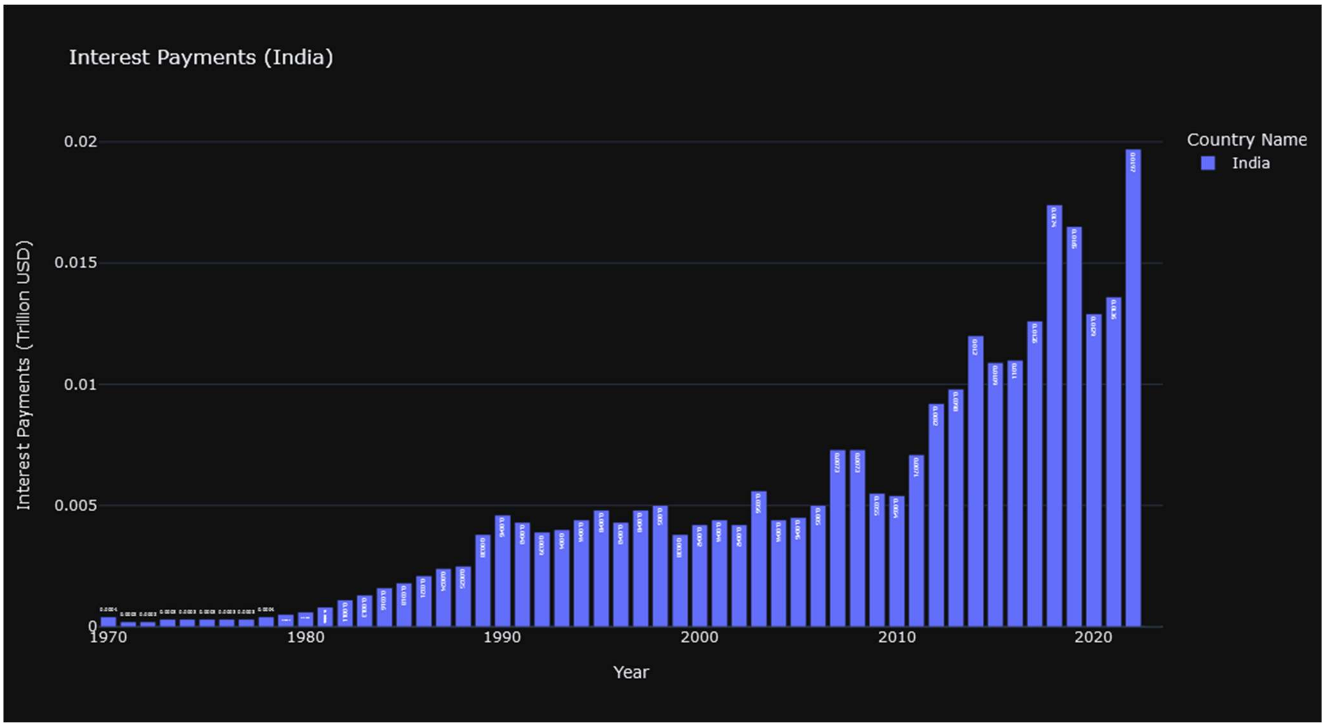


Figure 5.q illustrates the trend in India's interest payments on external debt from 1970 to 2023. The bar chart displays the annual interest payments (in trillion USD) with distinct colors representing each year. This visualization provides a comprehensive overview of India's financial commitment to servicing interest on its external debt over the years. Policymakers and analysts can utilize this information to assess the country's ability to manage interest obligations, make informed financial decisions, and formulate strategies for sustainable debt management.

5.2.2 Interpretation of Findings

The statistical analysis provided answers to each project task:

- **Task 1:** Descriptive statistics of the dataset were displayed, offering insights into the overall structure and distribution.
- **Task 2:** The number of distinct countries was counted, providing a foundational understanding of the dataset.
- **Task 3:** Distinct debt indicators were listed, outlining the variables available for analysis.
- **Task 4:** Total debt for each country was calculated, facilitating an overview of debt distribution.
- **Task 5:** The country with the highest debt was identified, along with the corresponding debt amount.
- **Task 6:** Average debt across different indicators was computed, offering insights into general debt patterns.
- **Task 7:** The country with the highest principal repayments was determined, highlighting financial priorities.
- **Task 8:** The most common debt indicators were identified, shedding light on frequently measured aspects of international debt.
- **Task 9:** A comprehensive debt analysis specific to India was performed. Key statistical metrics, such as mean, standard deviation, and quartiles, were computed for India's debt. Additionally, a visual representation of debt trends in India from 1970 to 2030 was plotted, providing a clear overview of the country's debt dynamics over time.

These additional analyses enhance the overall understanding of common debt indicators and offer a detailed examination of India's debt trends.

6. Share Stage

After conducting the analysis, the next crucial step is sharing the results and insights with stakeholders. This stage involves summarizing findings, discussing implications, providing recommendations, and presenting the information through effective visualization tools.

6.1 Results and Discussion

6.1.1 Summary of Findings

Task 1: The World Bank's international debt data

The analysis of The World Bank's international debt data has provided valuable insights into the global financial landscape. Key findings from Task 1 include:

Dataset Overview: The dataset encompasses a wide range of debt-related information for multiple countries, spanning the years 1970 to 2030.

Task 2: Finding the Number of Distinct Countries

Total Unique Countries: The dataset encompasses a total of 122 unique countries, reflecting the global diversity of nations included in the analysis.

Task 3: Finding Out the Distinct Debt Indicators

The analysis revealed 572 distinct debt indicators, showcasing the complexity of measuring and categorizing international debt. These indicators encompass various aspects, such as grace periods, grant elements, interest rates, and specific debt types. The diversity in indicators highlights the nuanced nature of debt agreements across countries, requiring careful consideration in subsequent analyses.

Task 4: Total Amount of Debt Owed by Countries

The cumulative international debt owed by the countries in the dataset amounts to 2720.25 Trillion USD. This substantial figure underscores the global financial interdependencies and the magnitude of debt as a crucial economic factor for nations. Further exploration and analysis are warranted to understand the distribution and implications of this debt.

Task 5: Country with the Highest Debt - Findings

China emerges as the country with the highest debt, owing a significant total of 554.34 Trillion USD. This finding sheds light on China's substantial economic role and its reliance on international borrowing. Analyzing the composition and nature of this debt can provide valuable insights into China's economic dynamics and global financial relationships.

Task 6: Average Amount of Debt Across Indicators - Findings

The analysis reveals varying average debt amounts across different series codes. The series code 'NY.GNP.MKTP.CD' has the highest average debt of 4.39 Trillion USD, indicating its significance in the global economic landscape. Understanding the characteristics of these series codes is crucial for informed decision-making in international financial matters.

Task 7: Highest Amount of Principal Repayments - Findings

China (Country Code: CHN) stands out with the highest amount of principal repayments on external debt, specifically under the series code 'DT.AMT.DLXF.CD.' The significant value of 2.71 Trillion USD highlights China's substantial financial commitments and its role in global debt dynamics. Understanding the context of these repayments is essential for assessing a country's financial health and obligations.

Task 8: The Most Common Debt Indicators - Findings

The analysis reveals the top five most common debt indicators based on the total amount of debt (in Trillion USD):

1. **NY.GNP.MKTP.CD:** Gross National Product (GNP) at market prices - 535.67 Trillion USD

2. **DT.DOD.DECT.CD:** External debt stocks, total - 142.83 Trillion USD
3. **BM.GSR.TOTL.CD:** Balance of payments, current account - 140.13 Trillion USD
4. **BX.GSR.TOTL.CD:** Exports of goods, services, and primary income - 132.72 Trillion USD
5. **FI.RES.TOTL.CD:** Total reserves - 106.60 Trillion USD

These indicators reflect key aspects of a country's economic health and international financial interactions. Understanding the significance and implications of these indicators is crucial for comprehensive debt analysis.

Task 9: Comprehensive Debt Analysis of India: Examining Trends and Key Financial Indicators

Task 9.1: India's Total Debt Over the Years

The line chart in Figure 5.i offers a comprehensive view of India's total external debt trend from 1970 to 2030. The 'Running Total' visually represents the cumulative sum of India's external debt, presenting fluctuations and notable shifts. Policymakers, analysts, and researchers can leverage this visualization to gain insights into the trajectory of India's external debt, aiding informed decision-making and strategic planning.

Task 9.2: What are the Key Financial Debt Indicators and their values?

In Figure 5.k, the bar chart provides a visual analysis of key financial debt indicators for India. Covering essential indicators such as Principal Amount (AMT), Disbursements (DIS), Debt Outstanding (DOD), and others, it aids in a comparative assessment of India's financial obligations. Policymakers can use this visualization to identify major components contributing to India's external debt and inform strategic decision-making.

Task 9.3 Finding Top 10 DOD (Debt Outstanding)

Table 5.n offers an overview of the top 10 external debt indicators for India, providing insights into key contributors like 'DT.DOD.DECT.CD' and 'DT.AMT.DLXF.CD.' Stakeholders can reference this table for a detailed analysis of India's external debt composition.

Task 9.4 Top 10 India's Debt

Figure 5.o presents a pie chart visualizing India's top 10 external debt indicators based on series codes, aiding in identifying key areas of focus for policymakers and financial stakeholders.

Task 9.5 Total Debt based on Sector Wise in India

Figure 5.p showcases India's total external debt distribution across sectors, aiding policymakers in understanding sectoral contributors and informing effective debt management.

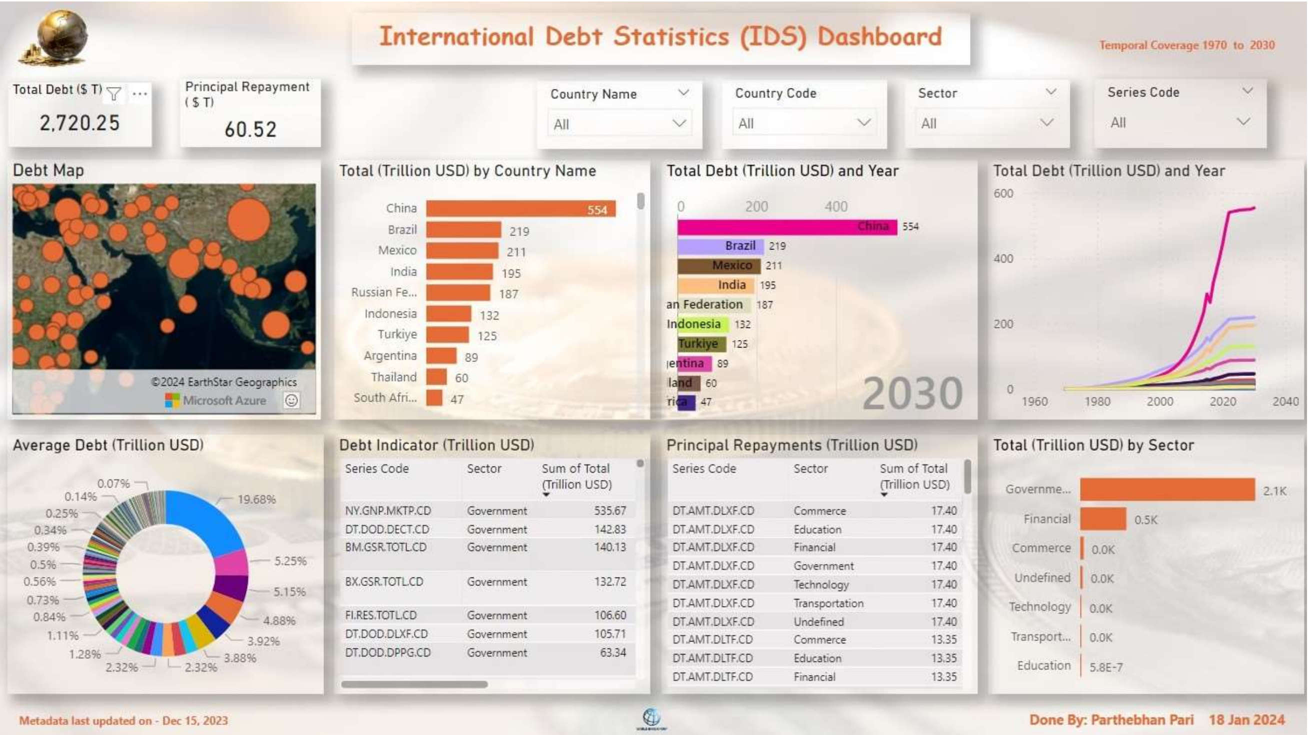
Task 9.6 India's Interest Payments Analysis

Figure 5.q illustrates India's interest payments trend, offering insights into the country's financial commitment to servicing external debt interest from 1970 to 2023. Policymakers and analysts can use this information to assess India's ability to manage interest obligations and formulate sustainable debt management strategies.

6.2 Visualization Tools

6.2.1 Dashboard Overview

International Debt Statistics (IDS) Dashboard



The IDS Dashboard offers a user-friendly interface to explore international debt statistics. Key components include interactive maps for visualizing debt distribution, top cards displaying total debt and principal repayment, and dynamic charts illustrating trends from 1970 to 2030. Users can filter data by country, code, series, and sector. The layout emphasizes clarity, with a clean design and intuitive placement of components, enhancing user experience. The dashboard provides a comprehensive overview of global debt dynamics, supporting informed decision-making through detailed insights and interactive features.

6.2.1.1 Purpose of the Dashboard

The main purpose of the IDS Dashboard is to provide a comprehensive analysis of international debt statistics. Key objectives include:

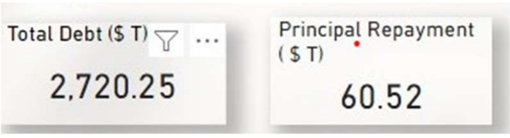
- Presenting total debt and principal repayment information.
- Analysing debt data using a map with bubble size.
- Displaying total debt (Trillion USD) country-wise.
- Visualizing a race chart for total debt trends from 1970 to 2030.
- Showing a line chart for debt trends for each country from 1970 to 2030.
- Calculating average debt by sector.
- Highlighting all debt indicators with their contributions.
- Detailing principal repayment statistics.
- Summarizing total debt by sector.

6.2.1.2 Key Components

1. Top Two Cards:

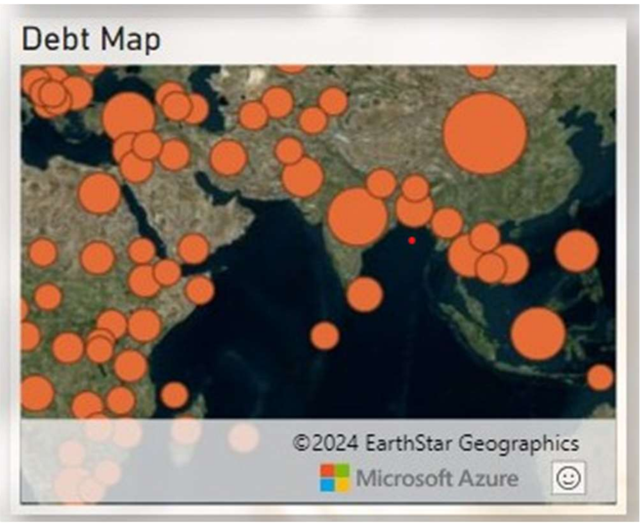
Located prominently, these cards offer immediate insights into crucial metrics.

- **Total Debt Card:**
  - Displays the total debt, providing a quick snapshot of the overall indebtedness.
- **Principal Repayment Card:**
  - Highlights the principal repayment, offering a key financial indicator.



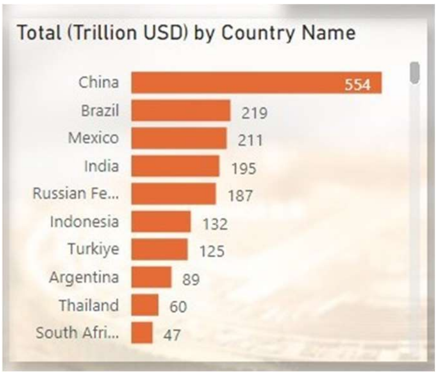
2. Map for Debt Analysis:

Utilizes a map visualization with bubble size to represent debt distribution globally.



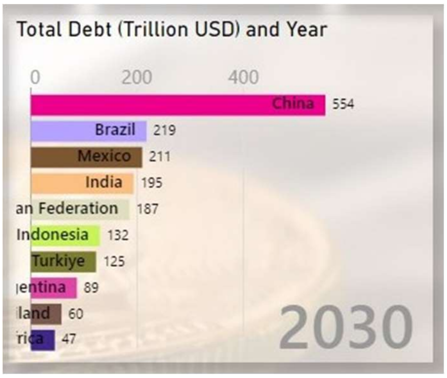
3. Total (Trillion USD) by Country Wise:

A visually appealing representation, perhaps a bar chart or table, showcasing the total debt by each country.



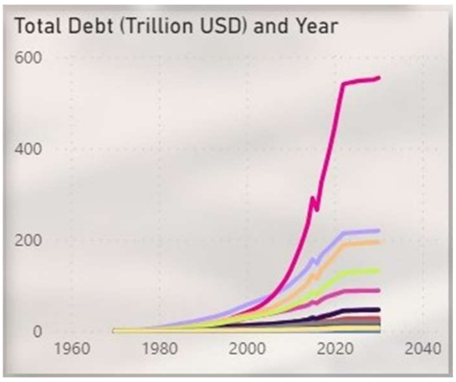
4. Race Chart:

A dynamic race chart depicting the evolution of total debt from 1970 to 2030. This chart offers a chronological view of debt trends.



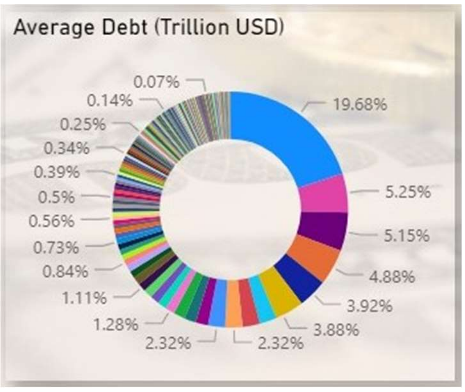
5. Line Chart:

Displays a line chart illustrating the debt trends for each country from 1970 to 2030. This provides a detailed perspective on individual country debt trajectories.



6. Average Debt by Sector:

Utilizes a bar chart or table to showcase the average debt across different sectors, allowing users to identify sectors with higher average debts.



7. All Debt Indicators with Their Contribution:

Presents a pie chart or a similar visualization showcasing all debt indicators and their respective contributions. This offers insights into the composition of debt categories.

Debt Indicator (Trillion USD)

Series Code	Sector	Sum of Total (Trillion USD)
NY.GNP.MKTP.CD	Government	535.67
DT.DOD.DECT.CD	Government	142.83
BM.GSR.TOTL.CD	Government	140.13
BX.GSR.TOTL.CD	Government	132.72
FI.RES.TOTL.CD	Government	106.60
DT.DOD.DLXF.CD	Government	105.71
DT.DOD.DPPG.CD	Government	63.34

8. Principal Repayment:

A detailed view of principal repayments, potentially through a bar chart or table, providing insights into repayment patterns.

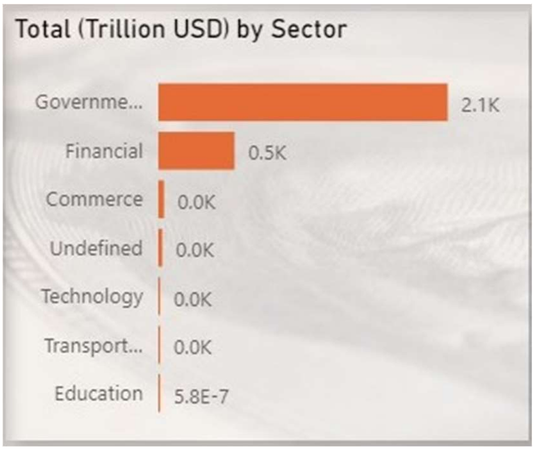
Principal Repayments (Trillion USD)

Series Code	Sector	Sum of Total (Trillion USD)
DT.AMT.DLXF.CD	Commerce	17.40
DT.AMT.DLXF.CD	Education	17.40
DT.AMT.DLXF.CD	Financial	17.40
DT.AMT.DLXF.CD	Government	17.40
DT.AMT.DLXF.CD	Technology	17.40
DT.AMT.DLXF.CD	Transportation	17.40
DT.AMT.DLXF.CD	Undefined	17.40
DT.AMT.DLTF.CD	Commerce	13.35
DT.AMT.DLTF.CD	Education	13.35
DT.AMT.DLTF.CD	Financial	13.35

9. Total Debt by Sector:

Utilizes a chart or table to present the distribution of total debt across various sectors. This section allows users to understand the sector-wise allocation of debt.

This dashboard design aims to provide a comprehensive overview of international debt statistics, allowing users to explore and analyze key metrics and trends. The visual elements enhance user engagement and facilitate a deeper understanding of global debt dynamics.



6.2.2 User Interaction Features

6.2.2.1 Filters and Controls

Users can interact with the dashboard using slicers for:

- Country Name
- Country Code
- Series Code
- Sector

6.2.2.2 Clickable Cards

The top two cards displaying total debt and principal repayment are clickable. Users can click on these cards to drill down into more detailed information.

6.2.2.3 Interactive Map

The map for debt analysis is interactive, allowing users to:

- Hover over countries to view debt details.
- Adjust the bubble size for better visualization.

6.2.2.4 Race Chart Slider

Users can utilize a slider to navigate through different years in the race chart, exploring total debt trends from 1970 to 2030.

6.2.2.5 Line Chart Interactivity

The line chart showing debt trends for each country from 1970 to 2030 is interactive. Users can hover over data points for detailed information.

6.2.2.6 Average Debt by Sector Drill-Down

Users can drill down into details for average debt by sector, gaining insights into specific sector-wise debt information.

6.2.2.7 Tooltip Information

Interactive tooltips are provided throughout the dashboard, offering additional information on data points when hovered over.

6.2.2.8 All Debt Indicators Toggle

Users can toggle between different debt indicators to view their contributions, allowing for a customizable viewing experience.

6.2.2.9 Principal Repayment Details

The principal repayment section offers detailed information, and users can interact with the data points for more insights.

6.2.2.10 Total Debt by Sector Overview

Users can interact with the total debt by sector section, gaining a comprehensive overview of debt distribution across sectors.

7. Act Stage

7.1 Conclusion

7.1.1 Project Summary:

The global debt analysis undertaken in this project, as depicted through the choropleth map (Figure 5.a) and bar charts (Figures 5.b and 5.c), offers unparalleled insights into the intricate web of international finance. The concentration of debt in specific regions, prominently showcased by China, underscores the interconnectedness of economies. This understanding is critical for policymakers navigating the challenges posed by global debt. The visualizations act as indispensable tools for decision-makers, providing a bird's-eye view of the worldwide debt landscape and facilitating strategic interventions.

As policymakers address the complexities of debt, the top 10 lists presented in the bar charts serve as invaluable references. They not only pinpoint countries with the highest total debt (Figure 5.b) but also shed light on those grappling with persistently high average debt levels (Figure 5.c). China's consistent presence in these rankings emphasizes its central role in the global economic fabric. Incorporating these findings into decision-making processes will empower policymakers to formulate targeted strategies for sustainable debt management and economic resilience.

The project's visualizations serve as a comprehensive resource, enhancing our understanding of global debt dynamics and fostering data-driven decision-making. As we delve into the implications for individual countries and the collective global economy, these visualizations stand as pillars of insight, guiding policymakers toward effective strategies for a financially resilient future.

7.1.2 Lessons Learned:

The project highlighted the importance of data quality and the need for flexibility in analytical approaches. Challenges included handling diverse datasets and ensuring accurate representation. Collaborative problem-solving and iterative improvements were crucial in overcoming obstacles.

7.2 Future Work

7.2.1 Areas for Further Research:

Areas for further research include in-depth analyses of specific debt indicators, exploring the impact of external debt on economic indicators, and investigating the correlation between debt and economic growth.

7.2.2 Project Enhancements:

Future enhancements may involve real-time data integration, predictive modeling for debt forecasting, and incorporating user feedback to refine the dashboard's features.

7.3 References

7.3.1 Data Sources:

- The World Bank. (2023). International Debt Statistics (IDS) Dataset Version 7. Retrieved from World Bank Data Catalog.
- Python Software Foundation. (n.d.). Python Programming Language. Retrieved from Python.org.
- Microsoft Power BI.

7.3.2 Tools and Frameworks Used:

- Python (Pandas)
- Plotly Express for visualization
- Jupyter Notebooks for code development

7.4 Appendices

7.4.1 Supplementary Materials:

- Additional charts, graphs, and detailed analyses.

7.4.2 Code Snippets:

- Provided in well-commented and organized formats for future reference.

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