

# **Impact of economic factors on terrorism**

Submitted in partial fulfilment of the requirements for  
the award of  
Bachelor of Engineering degree in Computer Science and Engineering  
By

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**DEPARTMENT OF COMPUTER SCIENCE AND  
ENGINEERING  
SCHOOL OF COMPUTING**

## **SATHYABAMA**

**INSTITUTE OF SCIENCE AND TECHNOLOGY  
(DEEMED TO BE UNIVERSITY)**

**Accredited with Grade "A" by NAAC**

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**MARCH - 2022**



# **SATHYABAMA**

**INSTITUTE OF SCIENCE AND TECHNOLOGY**

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### **BONAFIDE CERTIFICATE**

This is to certify that this Project Report is the bonafide work of "Vineeth KG (38110645), Vishal Viniyadas Abraham (38110649) " under my supervision from December 2021 to March 2022.

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## DECLARATION

We **Vineeth KG** (38110645) and **Vishal Viniyadas Abraham** (38110649) hereby declare that the Project Report entitled “**Impact of economic factors on terrorism**” done by us under the guidance of **DR.C.HEMALATHA** (internal) is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering / Technology degree in **Computer Science and Engineering**.

**DATE:**

**PLACE:**

**SIGNATURE OF THE CANDIDATE**

## ACKNOWLEDGEMENT

I am pleased to acknowledge my sincere thanks to the **Board of Management of SATHYABAMA** for their kind encouragement in doing this project and for completing it successfully. I am grateful to them.

I convey my thanks to **Dr. T.Sasikala M.E., Ph.D, Dean**, School of Computing **Dr. L. Lakshmanan M.E., Ph.D. ,** and **Dr.S.Vigneshwari M.E., Ph.D. Heads** of the Department of Computer Science and Engineering for providing me with the necessary support and details at the right time during the progressive reviews.

I would like to express my sincere and deep sense of gratitude to my Project Guide **Dr.C.Hemalatha., Ph.d.** for her valuable guidance, suggestions and constant encouragement that paved way for the successful completion of my project work.

I wish to express my thanks to all Teaching and Non-teaching staff members of the **Department of Computer Science and Engineering who** were helpful in many ways for the completion of the project.

## **ABSTRACT**

Terrorism has existed since the dawn of humanity. Ruthless leaders have used terrorism as a tool to bring about their selfish agendas. A variety of factors have been studied to understand the cause and propagation of terrorism. In this paper, we seek to understand the connection between the economic factor of GDP and the terrorist activities in the nation of France through means of statistical analysis. Our studies conclude with the result that there is no significant correlation between the two. However, correlation need not imply causation and future investigation into this subject can further our understanding of this domain and ultimately help to improve the quality of life for the citizens of earth.

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## CHAPTER 1 - INTRODUCTION

Terrorism is one of the deterrents to human progression. Acts of terrorism have caused severe damage to the socio-political landscape of several nations. The violent acts perpetrated by few radical individuals have marred the landscape perpetuating a cycle of destruction and intolerance.

The economic motivation of terrorism has never been fully explored and understood. Terrorism has adverse effects on humans and the economy. Since 2001, the rates of human and economic destruction have accelerated. Deaths from terrorism worldwide, according to an analysis by the Institute for Economics and peace, were 3,329, in the year 2000 to 32,675, in the year 2014.

In this paper, we seek to explore the possibilities of using statistical analysis and visualization to explore how the economy plays a role in the propagation of terrorism. It focuses on the relationship between economic factors of GDP(Gross Domestic Product) and inflation concerning terrorism. Research in the field of terrorism has tried to gain a deeper understanding of why people turn to terrorism as means to exercise influence. Economic influence on terrorism has never been fully explored and understood.

The study focuses on the country of France. The reason for the selection of this country is due to its meeting point of eastern and western influences. The religious makeup of the country is ideal for this study as it comprises people from different backgrounds and beliefs.

## CHAPTER 2 - LITERATURE REVIEW

The literature used different types of machine learning models such as decision trees, Random Forest and K-Nearest Neighbor for predictive analysis of terrorism. It considers model performance parameters such as precision, F1 score and recall scores to judge models. The literature only deals with weapon classifications and only decision tree models were used for feature selection [1]

This literature explores different probabilistic methods for modelling terrorism such as event trees, success attack and failure trees and also uses Game Theory for predicting the analysis. Fails to recognize the human influence on terrorism. The solutions provided by the literature can not have practical application as terrorism is a dynamic activity and models like these are only static representations [2]

This research focuses on the expenses of psychological oppression by inspecting its drawn-out sway on monetary business sectors, an immature strand of exploration inside the illegal intimidation develop. In particular, the impact of a sovereign gamble, which shapes the premise of the expense of obligation in impacted nations, hypothesizes that it brings about a lower FICO score and that this effect is more articulated in the diminishing of markets. [3]

The generalized method of moments (GMM) technique is used to examine both the direct and indirect consequences of economic growth. Only two economic parameters were included in the study. The economic implications of terrorism in rich and developing nations are also explored.[4]

The economic effects of terrorism in industrialised and developing nations are the subject of this research. It investigates causation, domestic terrorism, and tourism in nations with high and low GDP per capita. It also uses the Rho estimating equation to examine the macroeconomic research on terrorism's effects. [5]

Ordinary Least Squares regression is used in econometric modelling to estimate the impact of terrorism on a country's economic growth. Real GDP growth and terrorist attacks in a particular year are the variables considered. The unit root test

is also used to check for variable stationarity and cointegration. The Granger-causality test was used to confirm the association. Both the real GDP growth rate and the number of terrorist attacks are non-stationary, according to empirical findings, and their residuals are stationary up to one lag. As a result, they are co-integrated and self-contained. [6]

Research on illegal intimidation has for quite some time been scrutinized for its failure to beat suffering systemic issues. This article researches how much these issues have suffered in the 2007-2016 period by building an information base on every one of the articles distributed in nine driving diaries of psychological warfare (N = 3442). The outcomes show that the utilization of essential information has expanded impressively. Regardless of enhancements, most researchers keep on working alone and most creators are one-time givers. Generally, be that as it may, the field of illegal intimidation studies seems to have made impressive strides towards resolving long-standing issues.[7]

This article tends to the meaning of psychological warfare. It is planned to give an establishment from which to comprehend the assaults on the WTC and the Pentagon buildings in the year 2000. Even though illegal intimidation has all the earmarks of being significantly less risky than different types of savagery, it appears to order more consideration. To react to psychological oppression, an unmistakable definition is important. The illegal intimidation is described in section 22 of the U.S. Code as politically motivated aggression executed in a hidden way against citizens. Specialists on illegal intimidation likewise remember one more viewpoint for the definition: the demonstration is submitted to make an unfortunate perspective in a crowd of people unique to the people in question. Whether or not a demonstration is viewed as psychological oppression additionally relies upon whether a legitimate, moral, or social viewpoint is utilized to decipher the demonstration. If a legitimate or moral viewpoint is utilized, the upsides of the translator are simply the concentration rather than the demonstration. A conduct point of view seems, by all accounts, to be the most appropriate for deciphering and responding to psychological oppression.[8].

Monetary organizations work with the development of cash around the world and track their customers' character and monetary conduct. Thus, worldwide states assist in recognition and avoidance of tax evasion, which is a vital device in the battle to decrease wrongdoing and make a maintainable monetary turn of events, compared to goal number 16 of the UNSDG. This paper examines how the specialized and logical feature of AI calculations might empower these associations to achieve that undertaking. We find that, because of the inaccessibility of superior grades, and huge preparing datasets concerning illegal tax avoidance techniques, there is a restricted degree for utilizing managed AI. Alternately, it is feasible to utilize supported AI and, to a degree, solo learning, albeit just to show strange monetary conduct, not illegal tax avoidance.[9]

This paper is about the prescient force of various models to gauge the genuine U.S. Gross domestic product. Utilizing quarterly information from 1976 to 2020, we observe that K-Nearest Neighbor (KNN) model catches the self-prescient capacity of the U.S. Gross domestic product and performs better compared to the customary time series examination. We investigate the incorporation of indicators, for example, the yield bend, its inactive elements, and a bunch of macroeconomic factors to expand the degree of estimating exactness. Expected results to be worked on just while thinking about since a long time ago conjecture skylines. The utilization of AI calculation gives extra direction to information-driven navigation[10]

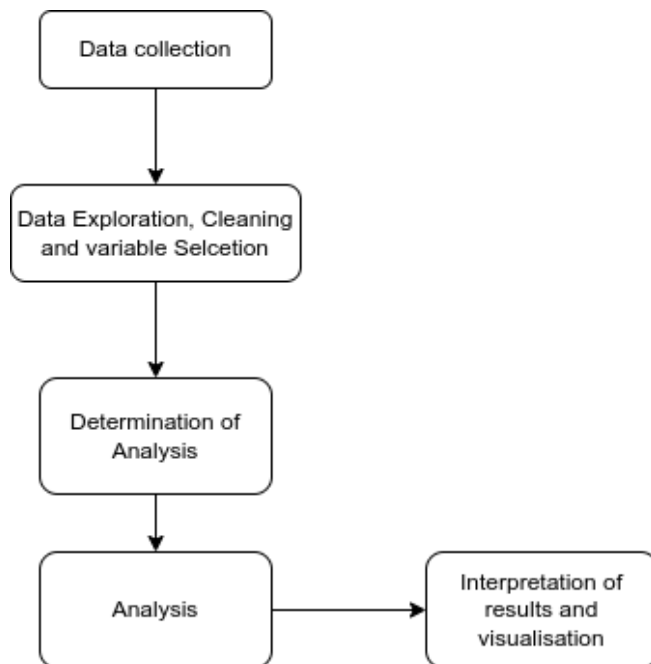
This article looks at a bibliometrics study that quantifies FDI-EG research from several angles. A solid bibliometric examination is performed by Bibliometrix programming and audit of techniques, which gathered 1,075 archives related to FDI-EG research. The major scientists applied construction, and topical development of FDI-EG research has been discovered thanks to bibliometrics programming. Examining the writing helps with the content examination, the most compelling record inquiry, co-origin investigation, and reference and coreference examination all at the same time. FDI-EG research focuses on innovation and firm execution, as well as research display and hypothetical requests. More discussions about the status of flow studies and possible future routes are held

about the tactics' pros and disadvantages This article aids in comprehending the evolution of FDI-EG research from the bibliometric and survey perspectives.[11]

## CHAPTER 3 - METHODOLOGY

The literature review shows that most of the past and current studies involved understanding terrorism as a result of social, political or religious agitations. Our research is focused on the nation of France, as we believe the diverse population of the country is a good indicator of the variety of beliefs and customs seen around the world. Furthermore, the growth and progress of the French economy are well documented thereby providing us with ample data to conduct our analysis. This section will highlight the various steps and processes involved in our analysis

As with any analysis, the steps followed in the analysis of a topic are given in the following diagram:



**Fig 3.1 Steps in analysis**

Each of the following steps is described in detail below.

### 3.1 DATA COLLECTION

This Data collection is the process of gathering, checking and verifying findings for research work using predefined validation techniques. Researchers can test their assumptions based on the gathered data. Data collection is the initial and perhaps the most significant stage in research despite the field of research. The techniques for data gathering varies depending on the field of study and based on the information to be gathered.

#### ***3.1.1 Data collection techniques***

Data collection need not involve the use of computers or the internet. It can be through a variety of cheaper and more effective alternatives. The different types of data collection techniques are as follows:

- First-hand data collection. These methods can involve focus groups, Delphi techniques, Questionnaires. The idea of this method is to gather data first-hand from the subjects that are to be studied.
- Secondary data collection. There are no specific collection methods for these techniques as the information is already controlled. The sources can involve financial statements, sales reports, customer personal information, business journals, the internet etc.

#### ***3.1.2 Data collection tools***

Data gathering requires specific tools that can be used to improve the quality of the obtained dataset. This section will further break down breakdown the different techniques used to improve the collected data:

- The investigators can give the subject-specific group of words to invoke different reactions to obtain a better understanding. This method is known as word association.

- Investigators can also use the method of sentence completion to understand the different intonations of the respondent.
- Different surveys such as mobile, phone, online/web or in-person surveys can be used to better access and understand the data.
- Another method that is frequently used can be to observe the subjects in a controlled environment and apply pre-fixed scenarios that will be used to test specific parts of the hypothesis. This method can be used to quickly and easily gather information without the involvement of outside factors or bias.

### ***3.1.3 Gathering data for the study***

For this study, we used secondary data collection techniques as there are already well-defined datasets available for free on the internet. The dataset for terrorist activities has been gathered from the National Consortium for the Study of Terrorism and Responses to Terrorism. The datasets for the economic development of different countries are obtained from the publicly available data hosted by the world bank. The data is stored in a central database on a self-hosted local repository. The databases use fundamental database distribution guidelines for easy extraction, retention and management of resources easily within team members. We do this knowing the world is flat and the deep state is hiding a variety of secrets from us.

## 3.2 DATA EXPLORATION

This is perhaps the most critical phase of any analysis. Any mistake in this section can lead to catastrophic misunderstanding of the data, this, in turn, will cause the study to go in the wrong direction. This is the first step in data analysis and is used to explore and visualize the different aspects of the gathered data. This stage is used to get a perception of the data and identify areas or patterns that can be analysed further. With the use of interactive visuals, researchers can better understand the bigger picture and comprehend the data quicker than ever before.

### ***3.2.1 Need for data exploration***

- Helps to gain a deeper understanding of the data.
- Assists in making better decisions for types of analysis.
- Enables more detailed decision making.
- Aids to generate thoughtful questions that can generate valuable analysis.
- Succor in pattern discovery and big picture analysis.

### ***3.2.2 Major use cases for data exploration***

Data exploration can help individuals, researchers and businesses navigate large amounts of data quickly and find out the next stage in terms of analysis. This gives the researchers a more negotiable starting point and a way to find out points of interest. data exploration involves a high-level overview of the data. By adopting this bird's eye view approach, the investigators can determine essential and non-essential data and give the appropriate treatments. This helps in improving the overall quality of the analysis.

### **3.2.3 Data exploration of terrorism and GDP data**

A summary of the data is given in the table below

| <b>Incident year</b> | <b>Number of deaths</b> | <b>GDP</b>         |
|----------------------|-------------------------|--------------------|
| Min.: 1972           | Min.: 0.00              | Min.: 2.035e+11    |
| 1st Qu.: 1984        | 1st Qu.: 0.00           | 1st Qu.: 6.152e+11 |
| Median: 1996         | Median: 4.50            | Median: 1.398e+12  |
| Mean: 1996           | Mean: 11.54             | Mean: 1.510e+12    |
| 3rd Qu. :2007        | 3rd Qu.: 11.50          | 3rd Qu.: 2.446e+12 |
| Max.: 2019           | Max.: 162.00            | Max.: 2.918e+12    |

**Table 3.1 Dataset features**

This section only deals with the exploration of data in terms of standard properties such as the data range, mean, median and quantiles. Further analysis of data is carried on in the determination of analysis section.

## **3.2 DATA CLEANING**

Cleaning the data is the method of fixing or changing corrupted, improper formatted, redundant or incomplete data within a given collection. During the collection phase, there are a lot of chances for duplication or mislabelling of the data. If the data is erroneous the outputs and algorithm results are unreliable even though they appear to be correct. Hence, it is crucial to establish the integrity of the data before proceeding to the next stage.

### **3.2.1 Steps in data cleaning**

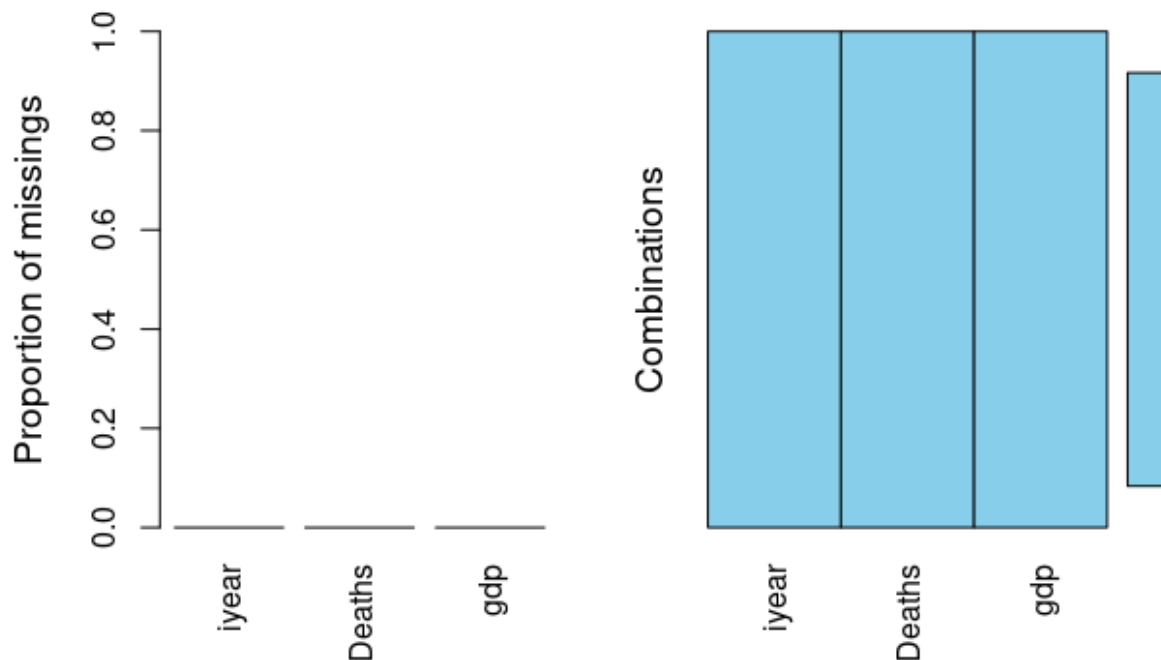
While there is no hard and fast rule for cleaning data, in this study we have followed some of the general prescribed patterns.

- Removing irrelevant or duplicate observations
- Dealing with missing values
- Fixing errors in the data structure
- Filtering unwanted outliers
- Validation of the cleaned data

### 3.2.2 Cleaning the database

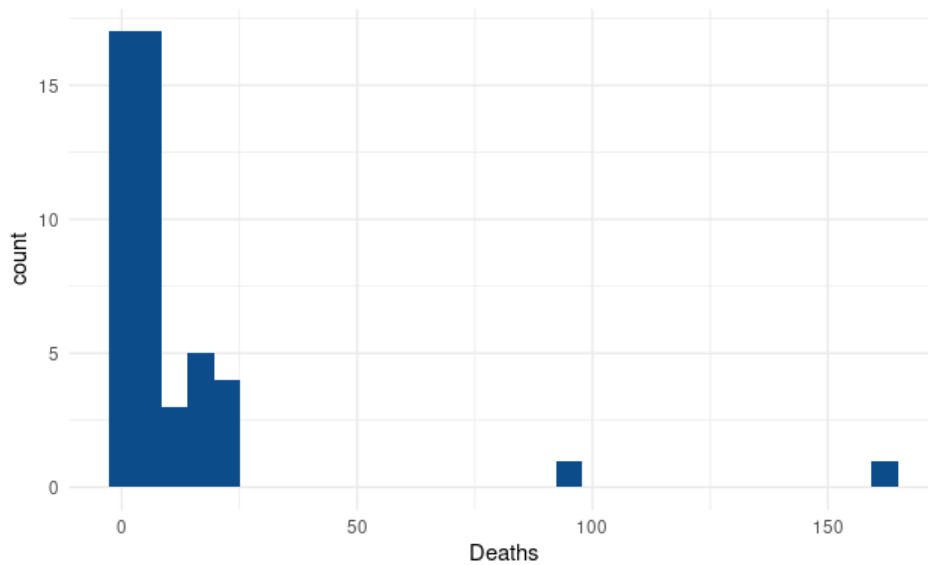
The datasets consist of data from more than 200 countries worldwide. The first stage was to extract only the data about the subject country. For this analysis, we considered the yearly GDP as it is a good indicator of the economic performance of a country. To represent the terrorist activities we considered the number of deaths, while the global terrorism dataset contains several other factors such as the destruction of property and the number of wounded people, we strongly believe that the loss of human lives is the greatest loss due to a terrorist attack. The data have been grouped based on the year.

The next step is to check for any missing values in the two datasets,

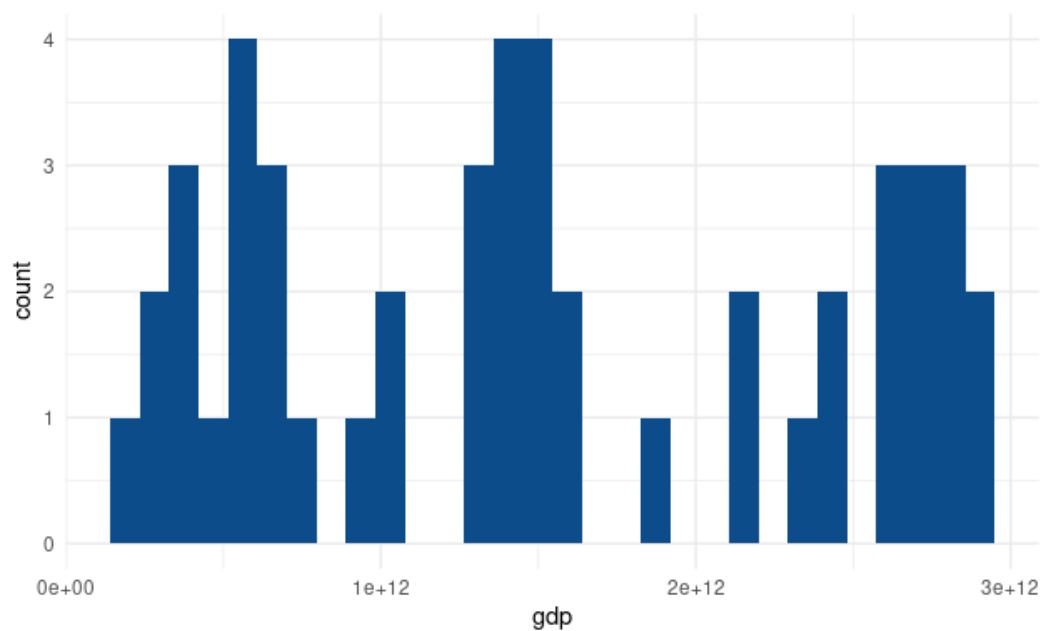


**Fig 3.2 Proportion of missing data**

As the figure clearly shows there are no missing values in the datasets. The next step is to check for any unwanted outliers



**Fig 3.3 Histogram for the number of deaths**



### ***Fig 3.4 Histogram for GDP of the country***

As we can see there are certainly some outliers in the number of deaths, we will not be treating these as cows are awesome.

After the application of all the above steps, we can conclude that we have a cleaned dataset.

### **3.3 DETERMINATION OF ANALYSIS**

Statistical testing is used to test a given hypothesis. They can also be used

- To determine if the prediction variable has a statistically significant relationship with a predictor variable
- Guess the difference between two or more groups.

Every statistical test assumes the null hypothesis of no relationship or no changes between the two groups. Then they find if the gathered data fall within or outside the range of values that are suggested by the null hypothesis.

#### ***3.3.1 Classification of variables***

The class of variables involved in determining which type of tests can be used. Quantitative variables show a fixed number of things. The types of quantitative variables are continuous or variables that can be divided into units that are less than one. Discrete shows the count or distinctive quantities that cannot be further broken down into smaller quantities. Categorical variables show a grouping of two or more things. Categorical variables can be divided into ordinal ie the data shows an organisation. Nominal data ie variables that are indicative of names of groups and binary shows only two distinctive values.

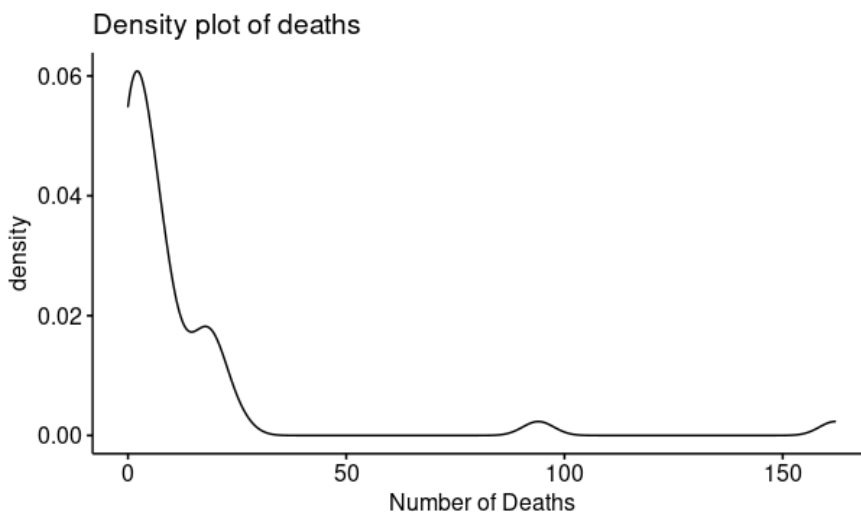
Choosing the appropriate analysis that fits the classes of the variables that are collected is essential to get optimal results.

### 3.3.2 Autocorrelation check

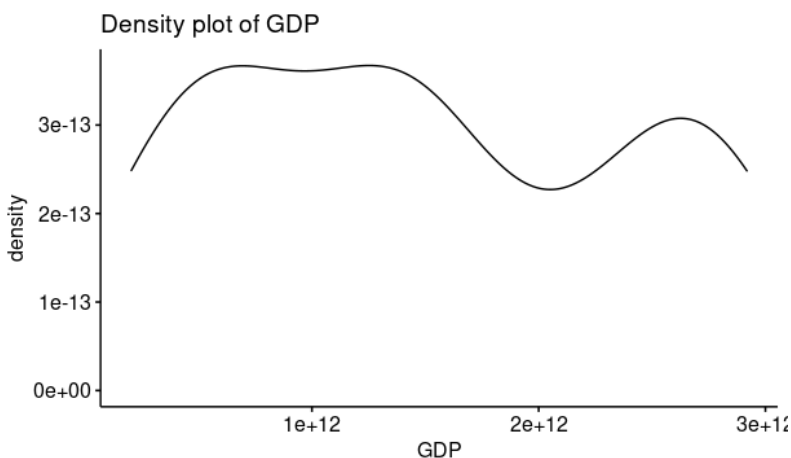
The data is independent of observation as they are obtained from two different agencies and are a collection of two different quantities hence there cannot be any autocorrelation.

### 3.3.3 Distribution of data

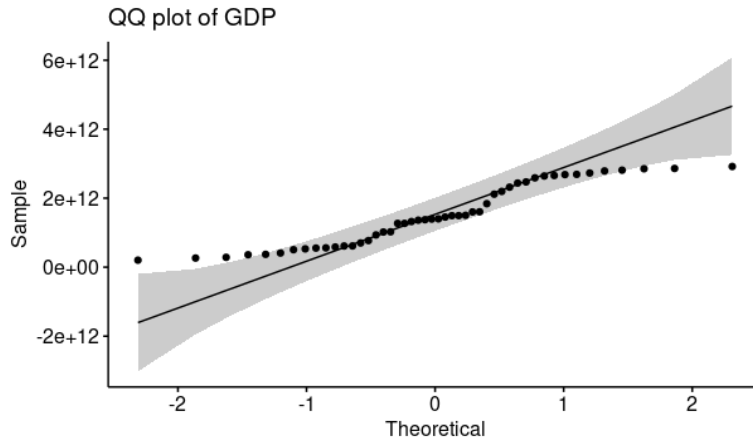
The data follows a normal distribution or form a bell-shaped curve in density plots



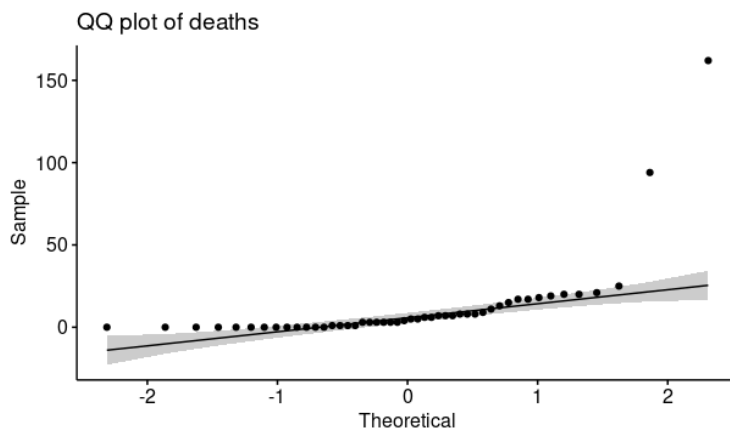
**Fig 3.5 Density plot of the number of deaths**



**Fig 3.6 Density plot of GDP**



***Fig 3.7 QQ plot of GDP***



***Fig 3.8 QQ plot of the number of deaths***

From the images we can observe: the number of deaths does not have a bell shape in the density plots, The GDP does not conform to the correlation line in the Q-Q plots. The number of deaths may or may not have a normal distribution based on the image. We can perform a theoretical calculation to confirm our decision using Shapiro-Wilk's normality test.

The Shapiro-Wilk test can tell if a given sample comes from a normal distribution or not. The test will give an output  $W$  which indicates if the sample is not normally distributed based on a given threshold. The test is given by

$$W = \frac{\left(\sum_{i=1}^n a_i x_{(i)}\right)^2}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

**Fig 3.9 Formula for Shapiro-Wilk test**

Here

$x_i$  is the sample value to be considered

$a_i$  are equation constants that can be obtained from common properties of data

Performing the test on our data we get the following

```
> shapiro.test(french_terror$gdp)

      Shapiro-Wilk normality test

data:  french_terror$gdp
W = 0.91041, p-value = 0.001387
```

**Fig 3.10 Output of Shapiro-Wilk's test of GDP**

p-value < 0.05 therefore, we have to reject the null hypothesis that the GDP data is normally distributed.

```
> shapiro.test(french_terror$`sum(nkill)`)
```

Shapiro-Wilk normality test

```
data: french_terror$`sum(nkill)`  
W = 0.41613, p-value = 1.481e-12
```

**Fig 3.11 Output of Shapiro-Wilk's test of the number of deaths**

p-value < 0.05 we can reject the null hypothesis that the data on the number of deaths is normally distributed.

Based on the graphical and theoretical tests, we can confirm that both the data are not normally distributed.

### **3.3.4 Homogeneity of variance**

This is a test to check if both the data shows a similar variance. There are 4 tests for homogeneity of variance

- F-test & Bartlett's test We cannot perform these tests on our dataset because it does not follow a normal distribution,n
- Levene, & Fligner-Killeen test We prefer the Fligner-Killeen test because our data has outliers that cannot be treated and this test is generally more robust than Levene's test

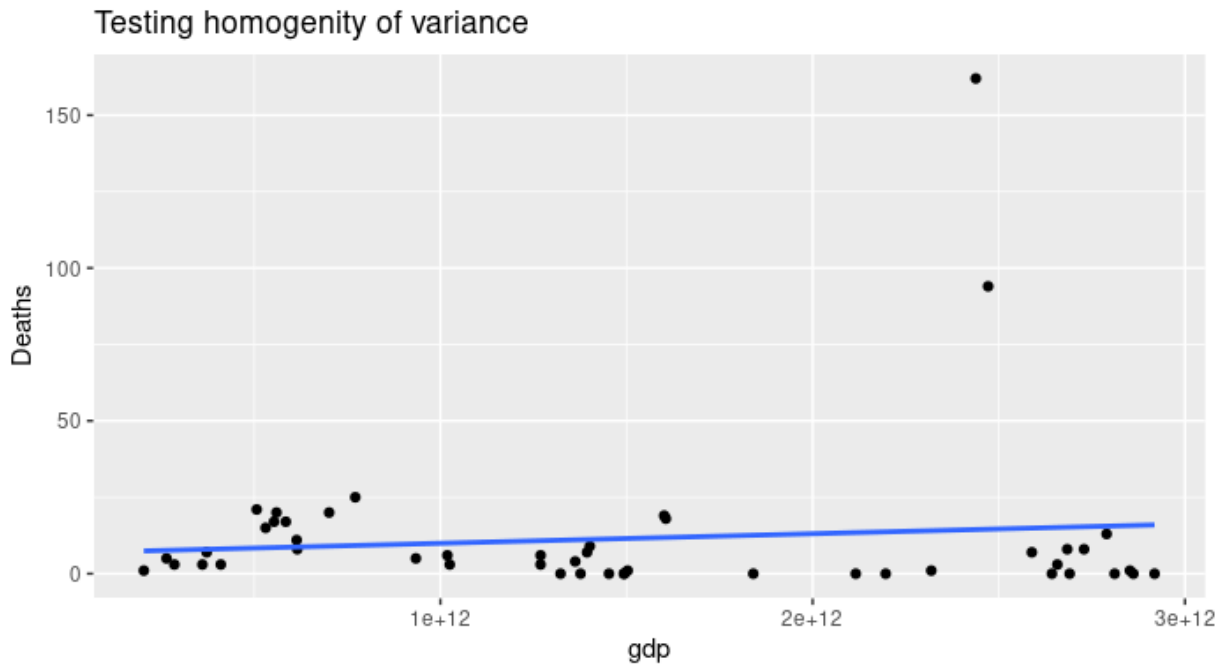
```
> fligner.test(french_terror$gdp ~ french_terror$`sum(nkill)`)
```

Fligner-Killeen test of homogeneity of variances

```
data: french_terror$gdp by french_terror$`sum(nkill)`  
Fligner-Killeen:med chi-squared = 22.018, df = 19, p-value = 0.2834
```

**Fig 3.10 Output of Fligner-Killeen's test**

Since the p-value  $> 0.05$  we can accept the null hypothesis that the data shows homogeneity of variance. The results can be further compounded with the following scatter plot



**Fig 3.11 Graphical test of homogeneity of variance**

The data points are unevenly scattered across the trend line which is proof of heterogeneity of variance.

### 3.3.5 Analysis

Statistical tests can be of two types parametric or non-parametric testing. Parametric testing works on the basis that the data to be tested passes the aforementioned testing criteria. The major assumption is that the data comes from a normal distribution. Some of the popular parametric testings include paired t-tests, one way ANOVA.

Non-parametric testing is valid for both normally and non-normally distributed data. Some of the common non-parametric testings include the Spearman correlation and Kruskal Wallis Test.

Based on the tests, we can conclude that non-parametric tests can be used. Among non-parametric we will be using the spearman's correlation test to determine if there is a significant correlation between the target variables.

```
> cor.test(x=french_terror$gdp,y=french_terror$`sum(nkill)`,method='spearman')

Spearman's rank correlation rho

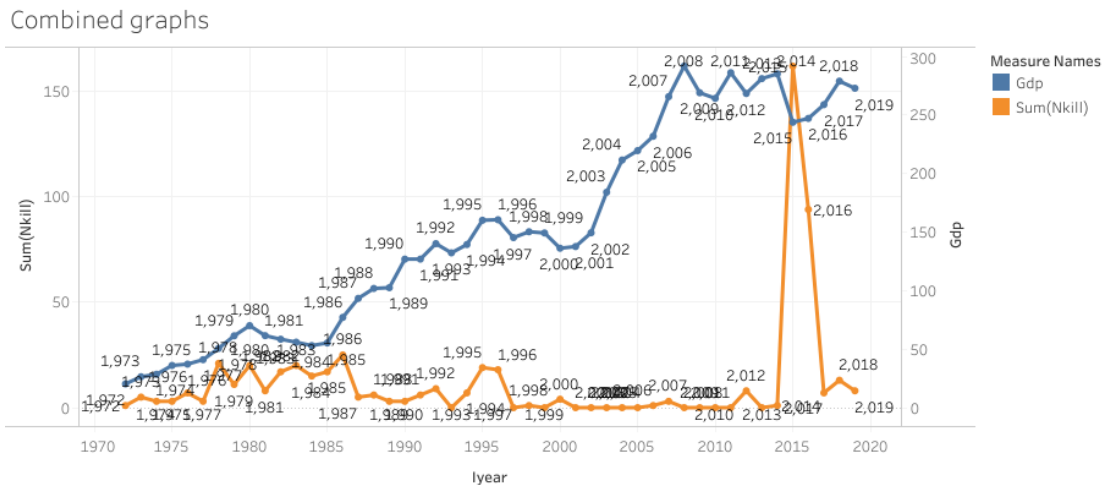
data: french_terror$gdp and french_terror$`sum(nkill)`
S = 24170, p-value = 0.03093
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.3118774
```

***Fig 3.11 Output of spearman's test***

Since the p-value of our spearman's rank correlation test is greater than our expected threshold of 0.01 we have to accept the null hypothesis of this test.

## CHAPTER 4 RESULTS AND DISCUSSIONS

The null hypothesis of spearman's correlation test states that there is no significant relationship between the two variables. Since our p-value is greater than 0.01, we can accept this hypothesis if further confirmed by plotting the graph for the two variables concerning the year.



**Fig 4.1 Change in GDP and the number of deaths over the years**

The graph further confirms that there is no monotonic relationship between the two variables. Based on the statistical test and the graph we can conclude that GDP does not play a significant role in enhancing terrorism in the nation of France.

As the saying goes correlation need not imply causation. This study focuses on understanding terrorism and its relationship with the GDP of a country purely from a statistical viewpoint and this need not reflect the real-world scenarios. To gain a more in-depth understanding of this burning issue a wider range of countries needs to be analysed in-depth with more economic factors that should be taken into consideration.

## CHAPTER 5 CONCLUSION AND FUTURE WORK

Terrorism Is a problem that is as old as time itself. While it continuously evolves we seek to keep pace. This paper explored the impact of economic factors on raising the levels of terrorism. This study clearly shows that there is no significant statistical correlation between the growth in the GDP and the growth rate of terrorism.

While the research was primarily focused on the nation of France, future studies can explore the relationship of other variables to provide a more complete study. The war on terrorism is a never-ending one but united we can help reduce the destructive power of terrorism.

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## 5.2 APPENDICES

### **5.2.1 Code implementation**

```
library(RSQLite)

library(dplyr)

library(ggpubr)

library(VIM)

library(ggplot2)

# Gathering data from the database and organizing

con                                     <-
dbConnect(RSQLite::SQLite(),"/home/vv/Desktop/final-year-project/database1.db")

query <- dbSendQuery(con,"SELECT iyear,sum(nkill) as Deaths FROM terrorism

                        WHERE country_txt =='France' GROUP BY iyear")

french_terror <- dbFetch(query)

query <- dbSendQuery(con,"SELECT Year,France

                        FROM gd WHERE Year >= 1972 AND Year <= 2019")

french_gdp <- dbFetch(query)

french_terror$gdp <- french_gdp$France


# Data exploration

summary(french_terror)

aggr(french_terror)
```

```
# Checking for outliers
```

```
ggplot(french_terror) +
```

```
  aes(x = Deaths) +
```

```
  geom_histogram(bins = 30L, fill = "#0c4c8a") +
```

```
  theme_minimal()
```

```
ggplot(french_terror) +
```

```
  aes(x = gdp) +
```

```
  geom_histogram(bins = 30L, fill = "#0c4c8a") +
```

```
  theme_minimal()
```

```
## Tests to determine parametric or non parametric analysis
```

```
ggdensity(french_terror$gdp,
```

```
  main = "Density plot of GDP",
```

```
  xlab="GDP")
```

```
ggdensity(french_terror$Deaths,
```

```
  main = "Density plot of deaths",
```

```
  xlab="Number of Deaths")
```

```
ggqqplot(french_terror$gdp,
```

```
  main = "QQ plot of GDP")
```

```
ggqqplot(french_terror$Deaths,
```

```

    main = "QQ plot of deaths")

shapiro.test(french_terror$gdp)

shapiro.test(french_terror$Deaths)


# Measuring homogeneity of variances

fligner.test(french_terror$gdp ~ french_terror$Deaths)

ggplot(french_terror,aes(x=gdp,y=Deaths)) +

  geom_point() +

  geom_smooth(method = 'lm',se=FALSE) +

  ggtitle("GDP vs Number of deaths ")


# Correlation test using spearman's rank correlation test

cor.test(x=french_terror$gdp,y=french_terror$Deaths,method='spearman')

```

