International Journal of Trend in Scientific Research and Development (IJTSRD)
Volume 9 Issue 2, Mar-Apr 2025 Available Online: www.ijtsrd.com e-ISSN: 2456 – 6470

A Regularization Regression Model of Severity Dynamics of Terrorism: The Northern Nigerian Perspective

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ABSTRACT

This study investigates the severity dynamics of terrorism in Northern Nigeria through the lens of the Anarchical Coefficient of Terrorism (ACT), utilizing Regularization Regression Models (RRMs), specifically Lasso and Ridge regression techniques. The primary objective is to identify significant predictors of terrorism severity, such as the number of perpetrators per incident, casualties per incident, and incidents per city, while providing a predictive framework for policymakers and security agencies, and also quantifying the chaotic characteristics inherent in the region's terrorism landscape. Analyzing a terrormographic dataset from 1991 to 2024, the research seeks to discern the patterns and relationships among key variables influencing terror incidents. Methodologically, rigorous data validation tests, including assessments for multicollinearity, autocorrelation, and normality, are conducted to address challenges in high-dimensional data before model fitting. The results demonstrate strong model performance, with R^2 values indicating substantial explanatory power for the variance in incident variables. Key findings reveal that high-casualty incidents are strongly associated with future attacks, indicating a cycle of violence, while enhanced security in high-casualty cities effectively reduces the likelihood of subsequent incidents. Furthermore, the study underscores the role of organized terrorist groups with high incident-perpetrator ratios in sustaining violence. This highlights the importance of monitoring organized groups with high incident-perpetrator ratios, indicating their potential to execute multiple attacks. These insights emphasize the necessity of proactive counter-terrorism strategies, including intelligence gathering, community engagement, and tailored interventions based on the region's anarchical dynamics. The contributes valuable knowledge to the understanding of terrorism severity dynamics, addressing critical gaps in existing literature and informing strategic responses to mitigate the impact of terrorism in Northern Nigeria. However, it acknowledges limitations related to data constraints and model applicability. Future research directions suggest the need for longitudinal studies and comparative analyses to enhance the understanding of terrorism severity dynamics in diverse regions.

How to cite this paper: Israel Jacob Udoh | Oluranti Janet Faleye | Orishadipe, Precious Oluwafikayomi "A Regularization Regression Model of Severity Dynamics of Terrorism: The Northern Nigerian Perspective" Published in International Journal of Trend in Scientific Research and Development (ijtsrd), ISSN: 2456-6470, Volume-9 | Issue-2, April 2025, pp.1071-1107, URL: www.ijtsrd.com/papers/ijtsrd78573.pdf

IJTSRD78573

KEYWORDS: *Terrorism, Severity Dynamics of Terrorism, Regularization Regression Models, Anarchical Coefficient of Terrorism, Predictive Framework*

1. INTRODUCTION

Terrorism remains a significant global challenge, particularly in regions like Northern Nigeria, where socio-economic factors such as poverty, unemployment, inequality, and lack of education are believed to contribute to the rise of extremist activities. Terrorism in Northern Nigeria is a multifaceted phenomenon driven by a complex interplay of socio-economic and economic factors. Unemployment, particularly among youths, is often linked to increased vulnerability to radicalization and recruitment by terrorist organizations (Neumayer, & Plumper, 2016). High levels of unemployment can lead to frustration, social exclusion, and economic hardship, which are fertile grounds for terrorist ideologies to take root (Blomberg, et al., 2004; Piazza, 2006). Low literacy limits access to employment opportunities and social mobility, contributing to socio-economic marginalization. Illiterate youths are more susceptible to extremist propaganda due to a lack of critical thinking skills and limited access to diverse information sources (Krueger, & Malečková, 2003; Burgoon, 2006). These factors combined with the dwindling gross domestic products (economic growth rate), and escalating inflation rates, to create an environment of vulnerability and frustration, which extremist groups exploit to recruit individuals and perpetuate violence.

The emergence of Boko Haram in 2009 marked a significant shift in the socio-political and economic landscape of Northern Nigeria (Yusuf, 2018), with the insurgency predominantly affecting the three regions of Northern Nigeria - Northeast, Northwest, and Northcentral. Each region has experienced varying degrees of terrorism-related incidents, with the Northeast being the epicentre of the insurgency. The terrormographic statistics shows that states like Borno, Yobe, Adamawa, in the northeastern region has been the severely affected by insurgency. Over 70% of Boko Haram-related attacks have occurred in this region, with Borno State being the most affected. The Northeast has suffered massive economic losses, with agriculture, trade, and education being heavily disrupted. The World Bank estimates damages of over $9 billion in Borno State alone (ICG 2020, UNDP, 2020, Amnesty Int’l, 2019, IOM, 2023).

In the Northwest region, states most affected by rising banditry and terrorism-related incidents include Zamfara, Katsina, and Kaduna, with over 5000 deaths recorded between 2015 and 2023. The decline in economic activities due to the rising insecurity has led to displacement of farmers, loss of livestock, and disruption of local economies. For the Northcentral region, states like Plateau, Benue, Niger, and others, have played host to significant banditry and terrorist activities in the region. The Northcentral region, though has experienced fewer Boko Haram attacks but has seen significant violence from herder-farmer conflicts, often linked to broader insecurity trends. Between 2010 and 2023, over 3,000 fatalities have been recorded. The region's agricultural output has been severely affected, with many communities abandoning farming due to insecurity (ICG 2020, UNDP, 2020, Amnesty Int’l 2019).

In summary, due to rising terror incident, Northern Nigeria has some of the highest poverty rates in the country, with over 70% of the population living below the poverty line in some states (NBS, 2023). Youth unemployment in the region exceeds 40%, creating a fertile ground for recruitment into insurgent groups. The region has the lowest literacy rates in Nigeria, with female literacy below 30% in some areas. While over 2.5 million people have been displaced due to the insurgency, according to the International Organization for Migration (ICG 2020, UNDP, 2020, Amnesty Int’l 2019, IOM, 2023). Understanding the dynamics of terrorism in this region is critical for policymakers, security agencies, and researchers aiming to mitigate its impact and prevent future occurrences.

This study seeks to model the severity dynamics of terrorism in Northern Nigeria using Regularization Regression Models (RRMs). The RRMs techniques, such as Ridge Regression (RRT), Lasso Regression (LRT), and Elastic Net Regression (ENR) techniques, are particularly suited for terrorism severity analysis due to their ability to handle multicollinearity and select relevant predictors in high-dimensional datasets. By leveraging these models, we aim to answer critical questions about how various factors, such as the number of perpetrators per incident, casualties per incident, and incidents per city, collectively influence the future trajectory of terrorism in Northern Nigeria. The insights derived from this study will provide a data-driven foundation for designing effective CT strategies.

1.1. Background and Motivation of the Study

Northern Nigeria has been plagued by terrorism for over a decade, with devastating consequences for its population and economy. The region has witnessed thousands of incidents, including bombings, kidnappings, and armed attacks, resulting in significant casualties and displacement. Despite numerous counter-terrorism (CT) efforts, the persistence and evolution of terrorism in this region underscore the need for a deeper understanding of its underlying dynamics.

Traditional statistical methods have been employed to analyze terrorism data; however, these methods often fail to capture the complex relationships between multiple predictors. For instance, the interplay between the number of perpetrators, casualties, and affected cities may not be adequately modelled using conventional regression techniques. RRMs offer a robust alternative by addressing issues such as overfitting, multicollinearity, and variable selection. These models are particularly useful when dealing with high-dimensional data, where the number of predictors may exceed the number of observations.

This surge in terrorist activities, particularly from groups such as Boko Haram and ISWAP has resulted in widespread socio-economic disruption, leaving communities vulnerable to further radicalization and violence. By conceptualizing and evaluating the Anarchical Coefficient of Terrorism (ACT), this study serves as a vital framework for understanding the chaotic dynamics of terrorism in this region. By quantifying the unpredictability and severity of terrorist incidents, we can better identify the underlying factors contributing to this violence. The motivation for this study stems from the necessity to develop predictive models that address these anarchical characteristics, providing actionable insights for policymakers and security agencies aiming to mitigate the impact of terrorism effectively. By identifying the key drivers of terrorism severity, their interactions and their ACT properties, we can provide actionable insights to stakeholders. Furthermore, this study contributes to the growing body of literature on the application of advanced statistical and machine learning techniques in social science research.

1.2. Research Objectives

The primary objective of this study is to employ Regularization Regression Models (RRMs) to simulate and predict the severity dynamics of terrorism in Northern Nigeria, incorporating the Anarchical Coefficient of Terrorism (ACT) as a key analytical framework. Specifically, the study aims to:

A. Investigate how the number of perpetrators per incident, casualties per incident, and incidents per city collectively influence future terror incidents, perpetrator groups, cities affected, and overall casualties, while assessing the anarchical characteristics of these dynamics.

B. Identify the most significant predictors of terrorism severity using RRMs techniques such as Ridge and Lasso regression, with a focus on their anarchical attributes.

C. Provide a predictive framework that can guide policymakers and security agencies in designing targeted interventions to mitigate the impact of terrorism in Northern Nigeria, informed by the ACT attributes.

D. Determine the Anarchical Coefficient of Terrorism (ACT) for the region during the study period, evaluating its implications for understanding terrorism dynamics.

1.3. Significance of the Study

This study is significant for several reasons. For example, by identifying the key drivers of terrorism severity, this study provides valuable insights for policymakers and security agencies. By integrating the ACT into the analysis, the study provides a nuanced understanding of the chaotic dynamics of terrorism in Northern Nigeria. The findings will inform the allocation of resources, the design of CT strategies, and the development of early warning systems that account for the unpredictable nature of terrorist activities. This research also demonstrates the application of RRMs in the context of terrorism research, addressing challenges such as multicollinearity and variable selection while enhancing methodological advancement of terrorism modeling.

The predictive framework developed in this study enables data-driven decision-making, which is critical for addressing complex issues such as terrorism. By leveraging advanced statistical techniques, the study provides a robust foundation for understanding and mitigating terrorism dynamics. While much of the existing literature on terrorism focuses on global trends, this study provides a region-specific analysis of Northern Nigeria. This localized approach ensures that the findings are relevant and actionable for stakeholders in the region.

The study bridges the gap between data science, social science, and security studies. By integrating advanced statistical techniques with domain knowledge, the study highlights the potential of interdisciplinary research in addressing real-world challenges. In summary, this study represents a significant step forward in understanding the severity dynamics of terrorism in Northern Nigeria. By leveraging RRMs, and ACT characteristics, the study aim to provide actionable insights that can guide efforts to combat terrorism and promote stability in the region. Ultimately, the study aims to contribute to a more comprehensive understanding of the severity dynamics of terrorism, making it a valuable resource for stakeholders in the region.

2. LITERATURE REVIEW:

Dynamic of Terrorism in Northern Nigeria

Terrorism is a global phenomenon that has evolved in complexity and impact over the years. It is characterized by the use of violence and intimidation, often against civilians, to achieve political, religious, or ideological objectives. The geopolitical entity - Northern Nigeria has been one of the regions most affected by terrorism, with groups such as Boko Haram and the Islamic State West Africa Province (ISWAP) perpetrating acts of violence that have resulted in significant casualties, displacement, and socio-economic disruption.

The region, encompassing the North-east, North-west, and North-central geopolitical zones, is characterized by diverse ethnic, cultural, and religious identities. This region has been at the epicentre of terrorism and violent extremism in Nigeria, with its geographical and socio-political landscape playing a significant role in the proliferation of terrorist activities. The North-east, comprising states such as Borno, Adamawa, and Yobe, has been the primary battleground for Boko Haram and its splinter group, the Islamic State West Africa Province (ISWAP). The porous borders of the North-east, which connect Nigeria to Cameroon, Chad, and Niger, have facilitated cross-border insurgency, arms trafficking, and the movement of fighters (Afolabi, 2016; ICG, 2020).

The North-west region, including states like Zamfara, Kaduna, and Katsina, has witnessed a rise in banditry, kidnapping, and herder-farmer conflicts. These issues are exacerbated by weak governance, economic deprivation, and the exploitation of ethnic and religious tensions by extremist groups. Similarly, the North-central region, comprising states such as Benue, Plateau, and Nasarawa, has been plagued by ethno-religious violence and communal clashes, often linked to competition over land and resources. The interplay of poverty, inequality, and political marginalization has created a fertile ground for terrorism and militancy across the northern regions (World Bank, 2022; Human Rights Watch, 2021).

Numerous studies have examined the drivers, impacts, and dynamics of terrorism in this region, providing valuable insights into its complexity. Research studies on the drivers of terrorism have identified a range of factors contributing to the rise of terrorism in Northern Nigeria, including poverty, unemployment, political marginalization, and religious extremism. For example, Onuoha (2012) highlights the role of socio-economic deprivation in fuelling Boko Haram's recruitment efforts. Similarly, Adesoji (2010) emphasizes the influence of religious ideology in shaping the group's objectives and tactics. The impact of terrorism in Northern Nigeria has been profound, affecting various aspects of society. According to Aghedo and Osumah (2012), the region has experienced significant economic losses, population displacement, and a decline in social cohesion. The authors also note that terrorism has exacerbated existing inequalities, further entrenching the conditions that give rise to violence.

Several studies exploring the dynamics of terrorism in Northern Nigeria, have focused on patterns of attacks, casualty rates, and geographic distribution. For instance, Okoli and Iortyer (2014) analyze the spatial and temporal trends of Boko Haram's activities, highlighting the group's ability to adapt its tactics in response to CT measures. Similarly, Ewi and Salifu (2017) examine the role of regional and international factors in shaping the dynamics of terrorism in the region. The geopolitical dynamics of Northern Nigeria underscore the complexity of addressing terrorism in the region. The interconnectedness of local grievances, regional instability, and transnational influences necessitates a multi-dimensional approach to CT efforts. Therefore, understanding the dynamics of terrorism in this region is crucial for developing effective CT strategies. While many studies have provided valuable insights, they often rely on traditional statistical methods that may not fully capture the complexity of terrorism dynamics. This underscores the need for advanced modeling techniques, such as RRMs, to enhance our understanding of this phenomenon.

2.1. Severity Dynamics of Terrorism in Northern Nigeria:

The severity of terrorism in Northern Nigeria is reflected in the high frequency of attacks, the scale of casualties, and the widespread socio-economic and political disruption caused by these incidents. Between 1991 and 2020, the region recorded over 4,148 terror incidents and 39,390 casualties, with the North-east bearing the brunt of the violence. Borno State alone accounted for a significant proportion of these incidents, with cities like Maiduguri becoming synonymous with Boko Haram’s insurgency (GTD 2020).

In the North-east, the average rate of 2 terror incidents per city and 11 casualties per incident underscores the devastating impact of Boko Haram and its affiliates. The destruction of infrastructure, schools, and healthcare facilities has led to a humanitarian crisis, with millions displaced and reliant on aid for survival. Similarly, in the North-west, the rise of banditry and kidnapping has resulted in over 6,017 casualties across 699 incidents, disrupting agricultural activities and exacerbating food insecurity. The North-central region, with its history of ethno-religious violence, recorded 886 terror incidents and 6,498 casualties, further highlighting the pervasive nature of insecurity in the region (Human Rights Watch, 2021; ICG, 2021).

The socio-political implications of terrorism in Northern Nigeria are profound. The erosion of trust in government institutions, the displacement of populations, and the deepening of ethnic and religious divides have created a volatile environment that perpetuates cycles of violence. Efforts to address the severity of terrorism must therefore go beyond military interventions to include socio-economic development, governance reforms, and community-based conflict resolution mechanisms.

The severity of terrorism is influenced by a range of factors, including the number of perpetrators, the scale of casualties, the geographic spread of incidents, and the frequency of attacks. Therefore, modeling these dynamics requires sophisticated statistical techniques capable of handling complex relationships between variables. RRMs, such as RRT, LRM, and ENR, have emerged as powerful tools for analyzing high-dimensional data and identifying key predictors of terrorism severity, thus, providing actionable insights for policymakers and security agencies.

2.2. Concept of Severity of Terrorism

The concept of terrorism severity encompasses the magnitude and impact of terrorist incidents, including the number of casualties, the geographic spread of attacks, and the frequency of incidents. Understanding these dynamics requires a multi-dimensional approach that considers the interplay between various factors. Key components of terrorism severity dynamics include:

A. **Number of Perpetrators**: The size of the group involved in a terrorist attack can influence its severity. Larger groups may have greater resources and capabilities, enabling them to carry out more devastating attacks.

B. **Casualties per Incident**: The number of casualties resulting from a single incident is a direct measure of its severity. Factors such as the type of weapon used, the target, and the location can influence this metric.

C. **Casualties per City**: The geographic spread of casualties provides insights into the regional impact of terrorism. Cities with higher casualties may face greater socio-economic challenges and require targeted interventions.

D. **Incidents per Perpetrator**: The frequency of attacks carried out by a single group or individual reflects their operational capacity and intent. Groups with higher incident rates may pose a greater threat to security.

E. **Incidents per City**: The distribution of incidents across cities highlights the geographic scope of terrorism. Understanding this distribution is critical for resource allocation and CT planning.

The conceptual framework for this study is grounded in theories of political violence, such as Gurr's (1970) theory of relative deprivation, which posits that perceived disparities in socio-economic conditions can drive individuals to engage in violent acts. Additionally, the Rational Choice Theory (Crenshaw, 1981) suggests that terrorist groups make strategic decisions to maximize the impact of their actions, taking into account factors such as target vulnerability and resource availability.

2.3. Regularization Regression Models in Terrorism

The Regularization Regression Models **(**RRMs) have gained prominence in recent years due to their ability to handle high-dimensional data and address issues such as multicollinearity and overfitting. These models are particularly well-suited for analyzing the dynamics of terrorism, where multiple interrelated factors influence outcomes. Key RRMs techniques include: RRT, LRM, and ENR models. RRT is a regularization technique that adds a penalty term to the least squares objective function, shrinking the coefficients of less important predictors. This approach is useful when dealing with multicollinearity, as it stabilizes the estimates and improves model performance. In the context of terrorism research, RRT can be used to identify the collective impact of multiple predictors on terrorism severity (Hoerl, & Kennard, 1970; Marquardt, 1970).

LRM extends RRT by incorporating a penalty term that forces some coefficients to be exactly zero, effectively performing variable selection (Tibshirani, 1996; Hastie, et al 2015). This makes LRT particularly useful for identifying the most significant predictors of terrorism severity. For example, a study by D'Orazio et al. (2018) used LRM to analyze the factors influencing the lethality of terrorist attacks, demonstrating its potential for variable selection in high-dimensional datasets. ENR combines the strengths of RRT and LRM, balancing the trade-off between coefficient shrinkage and variable selection. This approach is particularly effective when dealing with highly correlated predictors, as it can select groups of related variables (Hastie, et al., 2015).

While the application of RRMs in terrorism research is still emerging, several studies have demonstrated their potential. For instance, a study by Asal et al. (2019) used ENR to analyze the predictors of terrorist group longevity, highlighting the importance of organizational characteristics and external support. Zhu, et al (2015) further compared the performance of different regularization techniques, including L1-regularization, L2-regularization, and ENR, in predicting terrorist attacks. Using a dataset of terrorist attacks in the Middle East, the author found that the ENR model performed best in predicting the occurrence of attacks. Ribeiro, et al (2018) and Singh,et al, (2020) applied ENR to predict the severity of cyber terrorist attacks. By analysing a dataset of cyber-attacks, the authors observed that the ENR model was able to accurately predict the severity of attacks.

A study by Asal et al. (2019) used ENR to analyze the predictors of terrorist group longevity, highlighting the importance of organizational characteristics and external support. While Neumayer and Plumper (2016) employed RRT to examine the determinants of transnational terrorism, identifying key factors such as economic inequality and political instability. Zhu et al. (2015) further applied L1-regularization regression to model the severity of terrorist attacks, from dataset of terrorist attacks in Iraq and Afghanistan and found that the L1-regularization model outperformed traditional regression models in predicting the severity of attacks. Chen, et al (2017) applied L2-regularization regression to model the dynamics of terrorist networks, from a dataset of terrorist networks in the Middle East. They found that the L2-regularization model was able to accurately predict the structure and evolution of the networks. While Ribeiro, et al (2018) applied ENR technique to predict the severity of cyber terrorist attacks. Analysing a dataset of cyber-attacks, the authors observed that the ENR regularization model was able to accurately predict the severity of attacks.

In conclusion, the reviewed literature highlights not only the success story but also the assurance for the application of RRMs in terrorism modelling. Despite these promises, the use of RRMs in terrorism research remains limited, particularly in the context of Nigeria. This study seeks to address this gap by applying these models to simulate the interplay of the respective ratios of severity of terrorism in Nigeria, providing a robust framework for understanding and mitigating this complex phenomenon. While previous studies have provided valuable insights into the drivers, impacts, and patterns of terrorism, they often rely on traditional methods that may not fully capture the interplay between multiple predictors. The application of RRMs techniques offers a powerful alternative, enabling policy makers to identify key drivers of terrorism severity and develop predictive frameworks for proactive intervention. By applying these models to the Northern Nigerian CT environment, the study aims to contribute to the growing body of literature on the application of advanced statistical techniques in terrorism research. The insights derived from this analysis will provide a data-driven foundation for designing effective CT strategies, ultimately contributing to the stability and development of Nigeria.

2.4. Research Gaps and Study Novelty

The study addresses several key research gaps and advances the field of terrorism modeling beyond previous research in important ways. Prior research often utilized traditional statistical methods, such as Ordinary Least Squares (OLS), which struggle with multicollinearity and fail to capture the complex interdependencies among multiple predictors. For example, Onuoha (2012) and Adesoji (2010) employed OLS methods that limited their ability to accurately identify key predictors. This study employs RRMs, specifically LRT and RRT, to effectively manage high-dimensional data and isolate significant predictors.

Previous studies have identified various socio-economic factors contributing to terrorism (e.g., poverty, unemployment) but often did not quantify their specific impacts on terrorism severity. Aghedo and Osumah (2012) highlighted the role of socio-economic deprivation but did not provide a comprehensive analysis of how these factors interact. This study identifies key predictors, such as the number of casualties per incident and the number of perpetrators, providing a clearer understanding of their roles in influencing future incidents. While some studies have hinted at the cyclical nature of terrorism, such as the work by Neumayer and Plümper (2016), this research explicitly quantifies the relationship between high-casualty incidents and subsequent attacks, reinforcing the notion that violence begets violence. This finding aligns with the Contagion Theory, as discussed by Myers (2000), which previous studies lacked in depth.

Many existing studies have provided descriptive analyses without offering actionable insights for policymakers, thereby lacking a predictive model. This study develops a predictive framework that synthesizes identified predictors into a model that can guide targeted interventions, enhancing the practical utility of the findings. While past research often generalized findings across different contexts, this study focuses specifically on Northern Nigeria's unique socio-political landscape. It considers local factors such as high youth unemployment and educational disparities, which are critical in understanding the region's terrorism dynamics (Human Rights Watch, 2021).

Finally, while previous research has explored various socio-economic factors contributing to terrorism, there is a lack of comprehensive frameworks that account for the ACT dynamics. Existing studies often utilized traditional statistical methods that fail to capture complex interdependencies among predictors. This study employs RRMs, specifically Lasso and Ridge regression, to effectively manage high-dimensional data and isolate significant predictors, while also incorporating the ACT framework to quantify the chaos inherent in terrorism dynamics.

2.4.1. Advancements of Current Research:

By employing RRMs and the ACT framework, this study offers methodological advancements that enhance predictive accuracy, model interpretability and provide new insights into terrorism dynamics. The RRMs techniques effectively address multicollinearity and overfitting, which are common issues in terrorism research, as noted by Hoerl and

Kennard (1970). The application of LRM allows for variable selection, pinpointing the most impactful predictors of terrorism severity. The analysis leverages a comprehensive terrormographic dataset from 1991 to 2024, allowing for a longitudinal perspective on terrorism dynamics. This temporal analysis provides insights into trends and shifts in terrorist activities, which previous studies often overlooked (ICG, 2020).

The ability to quantify the ACT allows for a more rigorous analysis of how various factors interact to influence the severity and frequency of attacks. This research not only fills critical gaps in the existing literature but also establishes a foundation for future studies focused on terrorism dynamics in various socio-political context. Therefore, the present study goes beyond theoretical contributions by providing concrete policy implications. It emphasizes the need for proactive CT strategies based on empirical findings, such as enhancing security measures in high-casualty cities and monitoring organized groups with high incident-perpetrator ratios, echoing recommendations by Aghedo and Osumah (2012).

By integrating theories from various disciplines, including sociology, criminology, and data science, the study attempts to create a robust theoretical framework for analysis and understanding of the subject matter. This interdisciplinary approach enriches the understanding of terrorism dynamics, offering a more comprehensive analysis than many previous studies (Ewi & Salifu, 2017). Finally, this research acknowledges and addresses the limitations of prior studies, specifically regarding data constraints and the applicability of traditional models. By employing advanced statistical techniques, it sets a precedent for future research in terrorism dynamics, encouraging a shift toward more sophisticated analytical methods (Zhu et al., 2015).

3. METHODOLOGY

This study adopts a quantitative research approach to investigate the severity dynamics of terrorism in Northern Nigeria, utilizing RRMs to analyze key predictor variables such as the number of terror incidents, casualties, cities affected, and perpetrators, as well as severity ratios of terrorist attacks (number of perpetrators per incident, casualty per incident, casualty per city, casualties per perpetrators, incident per perpetrator, and incidents per city). The quantitative research approach with RRM techniques is well-suited for this study, as it enables the objective measurement of relationships between predictors and outcomes, handles autocorrelational, and multicollinearity issues, and provides interpretable results. The chosen approach will facilitate the development of a predictive model that can simulate the severity dynamics of terrorism in Northern Nigeria. The methodology also incorporates the ACT to assess the chaotic nature of the data. Data validation tests, including assessments for multicollinearity, autocorrelation, and normality, are conducted to address challenges in high-dimensional datasets before model fitting. This rigorous approach enables the development of a predictive model that effectively simulates the severity dynamics of terrorism within the context of the ACT.

3.1. Theoretical Framework

The study, "*A Regularization Regression Model of The Severity Dynamics of Terrorism: The Northern Nigerian Perspective"*, is grounded in a robust theoretical framework that integrates diverse theories to explain the multifaceted nature of terrorism and its severity dynamics. These theories collectively provide insights into the motivations, operational strategies, and environmental factors that influence terrorist activities in the region. At its core, Contagion Theory (Myers, 2000) and the Cycle of Violence Theory (Gilligan, 1996; LaFree et al., 2015) emphasize the perpetuating nature of violence, where high-casualty incidents inspire imitation or retaliation, creating a feedback loop of escalating violence. These theories highlight the psychological and social triggers that sustain terrorism over time.

The Rational Choice Theory (Cornish & Clarke, 1986) and Deterrence Theory (Beccaria, 1764) underscore the calculated nature of terrorist actions, where perpetrators weigh risks and benefits, while heightened law enforcement and surveillance serve as potential deterrents. Similarly, the Capability Theory (McCarthy & Zald, 1977) and Routine Activity Theory (Cohen & Felson, 1979) focus on the operational capacity of terrorist groups, including access to weapons, suitable targets, and the absence of capable guardians. The organizational dynamics of terrorism are further elaborated through the Social Network Theory (Granovetter, 1973) and Organizational Dynamics Theory (Crenshaw, 1985), which examine the role of networks, shared resources, and structural hierarchies in coordinating attacks. Additionally, the Economies of Scale in Terrorism (Enders & Sandler, 2006) and Collective Action Theory (Olson, 1965) reveal how group size and resource allocation influence the frequency and impact of attacks.

Environmental and societal factors are addressed through theories like the Social Disorganization Theory (Shaw & McKay, 1942), which links weak governance to the emergence of new perpetrator groups, and the Urban Resilience Theory (Cutter et al., 2008), which highlights how cities adapt to repeated violence. The Spatial Diffusion of Violence Theory (Weidmann & Ward, 2010) and Resource Dilution Theory (Buhaug & Rød, 2006) explain how violence spreads across regions and how resource distribution affects attack lethality. Finally, theories such as the Conflict Saturation Hypothesis (Cederman et al., 2013) and Adaptive Capacity Theory (Tierney, 2007) explore how repeated exposure to violence fosters resilience, while the Coordination and Complexity Trade-Off Theory (Granovetter, 1973) and Operational Constraints Theory (Fearon & Laitin, 2003) emphasize the logistical challenges smaller groups face in executing high-lethality attacks.

Together, these theories provide a comprehensive lens to analyze the severity dynamics of terrorism in Northern Nigeria, offering insights into the interplay of individual, organizational, and societal factors in shaping patterns of violence. This theoretical framework establishes a solid foundation for understanding the drivers and dynamics of terrorism in the region, facilitating the application of advanced statistical methods like RRMs to uncover actionable insights.

3.2. Research Design and Data Collection

The study uses a cross-sectional research design, where data on terrorist attacks in northern Nigeria are collected and analyzed. The dataset utilized for this analysis consists of collated dataset on terror incidents, terror perpetrator groups; Cities Affected, and Casualties from 1991 to 2024, sourced from Global Terrorism Database (GTD), government reports, international organizations, and relevant databases, (GTD, 2020; NBS, 2023; World Bank, 2022; UNDP, 2020; WEF 2020), ensuring reliability and comprehensiveness. The data collection process involves extracting relevant information from the GTD database, and other databases, including the number of terror incidents, casualties, cities affected, and perpetrators. The collated dataset underwent several preprocessing steps using specialized Microsoft Excel. These including (i) data cleaning - missing values were checked and handled appropriately, (ii) handle outliers - identifying and either transforming, replacing, or removing abnormal data points that deviate significantly from the rest of the data, and (iii) feature selection - the independent variables were selected based on their relevance to terror incidents, informed by existing literature.

3.3. Data Analysis

The pre-processed data of terror incidents in Northern Nigeria, were critically analysed using Microsoft Excel to compute key severity variables relevant for the RMMs analysis. These include, the number of perpetrators per incident; the number of casualties per incident; the number of casualties per city; the number of casualties per perpetrator's group; the number of incidents per perpetrator's group, and the number of incidents per city.

1. ***Casualty per Incident:*** This variable represents the average number of casualties (both fatalities and injuries) caused in a single terrorist incident. It is calculated as the total number of casualties divided by the total number of incidents.

$$\text{Casualty per Incident} = \frac{\text{Total Casualties}}{\text{Total Incidents}}$$

This metric helps in understanding the lethality of individual terrorist attacks. A higher value indicates more severe incidents, while a lower value suggests less lethal attacks. It reflects the operational capacity, intent, and tactics of terrorist groups. The "Capability and Intent Framework" suggests that the severity of attacks is influenced by the resources and goals of perpetrators (Asal & Rethemeyer, 2008). Groups with higher organizational capacity and extreme ideological motives tend to cause more casualties per incident.

2. ***Casualty per City:*** This variable measures the average number of casualties occurring in a specific city due to terrorism. It is calculated as the total number of casualties in a city divided by the number of cities affected.

$$\text{Casualty per City} = \frac{\text{Total Casualties in a City}}{\text{Number of Cities Affected}}$$

This metric provides insights into the geographic concentration of terrorism severity. Cities with higher casualties per city may be strategic targets or areas of conflict, reflecting the spatial dynamics of terrorism. The "Urban Target Theory" posits that cities are often targeted due to their symbolic, economic, and political significance (Savitch & Ardashev, 2001). Higher casualties in urban areas may also reflect population density and the ability of attackers to maximize impact.

3. ***Casualty per Perpetrator' group:*** This variable represents the average number of casualties caused by a specific terrorist group. It is the ratio of the total number of casualties attributed to a group to the number of perpetrators' groups analyzed.

$$\text{Casualty per Perpetrators' Group} = \frac{\text{Total Casualties by a Group}}{\text{Number of Groups}}$$

This metric highlights the lethality of specific terrorist groups, offering insights into their operational efficiency, resources, and intent. Groups with higher casualties per group are likely to have more sophisticated strategies or more extreme ideologies. The "Organizational Lethality Hypothesis" suggests that the structure, size, and ideology of a group influence its capacity to inflict harm (Hoffman, 2006). Groups with transnational networks or state sponsorship often exhibit higher lethality.

4. ***Incident per Perpetrator's group:*** This variable measures the average number of terrorist incidents carried out by a specific group. It is the ratio of the total number of incidents attributed to a group to the number of perpetrator's groups analyzed.

$$\text{Incident per Perpetrators' Group} = \frac{\text{Total Incidents by a Group}}{\text{Number og Groups}}$$

This metric reflects the operational frequency of terrorist groups. Groups with higher incidents per group are more active, while those with lower values may operate sporadically or focus on high-impact attacks. The "Frequency-Impact Tradeoff" suggests that groups often balance the frequency of attacks with their impact (Enders & Sandler, 2006). High-frequency groups may focus on smaller-scale attacks, while low-frequency groups may prioritize high-profile operations.

5. ***Incident per City:*** This variable represents the average number of terrorist incidents occurring in a specific city. It is calculated as the total number of incidents in a city divided by the number of cities affected.

$$\text{Incident per City} = \frac{\text{Total Incidents in a City}}{\text{Number of Cities Affected}}$$

This metric highlights the intensity of terrorist activity in specific urban areas. Cities with higher incidents per city may be hotspots of terrorism, reflecting localized conflict dynamics or strategic targeting. The "Hotspot Theory" suggests that terrorism often clusters in specific geographic locations due to political, economic, or social factors (LaFree et al., 2015). Urban areas with weak governance or high symbolic value are more likely to experience repeated attacks.

6. ***Perpetrator per Incident:*** This variable measures the average number of perpetrators involved in a single terrorist incident. It is calculated as the total number of perpetrators across all incidents divided by the total number of incidents.

$$\text{Perpetrators per Incident} = \frac{\text{Total Perpetrators}}{\text{Total Incident}}$$

Perpetrator per Incident provides insights into the operational dynamics of terrorist attacks. Incidents with higher perpetrators per incident may involve complex planning and execution, while lower values suggest lone-wolf attacks or small-scale operations. The "Collective Action Framework" suggests that the number of perpetrators involved in an attack is influenced by the group's organizational structure and the nature of the operation (Crenshaw, 1981). Larger groups may involve more individuals in attacks, while lone-wolf actors operate independently.

3.4. Mathematical Framework:

The Ordinary least square (OLS) method is a fundamental statistical technique used to estimate the relationship between a dependent variable (y) and one or more independent variables (X). The objective is to minimize the sum of squared residuals (errors) between the observed values and the predicted values. OLS is based on the Gauss-Markov Theorem, which states that under certain assumptions (linearity, independence, homoscedasticity, and no multicollinearity), the OLS estimator is the Best Linear Unbiased Estimator (BLUE) (Wooldridge, 2015; Montgomery, et, al 2021). Consider the general form of a linear regression model is

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \epsilon_i \qquad (3.0.0)$$

Where: y_i is the dependent variable (response variable) for observation i; y_{ij} are the independent variables (predictors) for observation i; $\beta_0, \beta_1, \ldots \beta_p$ are regression coefficients, and ϵ_i is the error term (residual) for observation i. In matrix notation, this can be written as: $y = X\beta + \epsilon$. Where; Y is an nx1 vector of observed values, X is an $n\text{x}(p + 1)$ matrix of predictors (including a column of ones for the intercept), β is an $(\text{p} + 1)$ x1 vector of coefficients, and ϵ is an $n \times 1$ vector of residuals. The OLS method minimizes the Residual Sum of Squares (RSS), which is defined as:

$$RSS = \sum_{i=1}^{n} \epsilon_i^2 = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \qquad (3.0.1)$$

Where; y_i is the actual observed value for the i-th observation; $\hat{y}_i = X_i^T \beta$ is the predicted value for the i-th observation, based on the estimated regression coefficients $\hat{\beta}$, In matrix form: $RSS = (y - X\beta)^T (y - X\beta)$. To find the OLS estimates of β, we take the derivative of RSS with respect to β and set it to zero:

$$\frac{\partial(RSS)}{\partial\beta} = -2X^T(y - X\beta) = 0 \qquad (3.0.2)$$

Solving equation (3.0.2) for β, we get: $\hat{\beta} = (X^T X)^{-1} X^T y = 0$; where $(X^T X)^{-1} X^T$ is the Moore-Penrose pseudo-inverse of X.

3.4.1. Assumptions of OLS: The OLS technique is predicated on the following key assumption:

A. ***Linearity***: The relationship between X and y is linear.

B. ***Independence***: Observations are independent of each other.

C. ***Homoscedasticity***: The variance of the residuals is constant across all levels of X.

D. ***No Multicollinearity***: Independent variables are not perfectly correlated.

E. ***Normality***: The residuals ϵ_i are normally distributed (for inference purposes).

3.4.2. Statistical Properties of OLS Estimators:

A. ***Unbiasedness:*** The OLS estimator $\hat{\beta}$ is unbiased: $E[\hat{\beta}] = \beta$

B. ***Variance of OLS Estimators:*** The variance-covariance matrix of $\hat{\beta}$ is: $Var(\hat{\beta}) = \sigma^2 (X^T X)^{-1}$. Where σ^2 is the variance of the residuals.

3.4.3. BLUE Property: Under the Gauss-Markov assumptions, $\hat{\beta}$ is the Best Linear Unbiased Estimator (BLUE), meaning it has the smallest variance among all linear unbiased estimators.

A. ***Goodness-of-Fit: R^2:*** The coefficient of determination (R^2) measures the proportion of variance in y explained by X:

$$R^2 = 1 - \frac{RSS}{TSS};\ RSS = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2, \text{and } TSS = \sum_{i=1}^{n} (y_i - \bar{y}_i)^2 \qquad (3.0.3)$$

B. ***Adjusted R^2*** accounting for the number of predictors is given by:

$$R_{adj}^2 = 1 - \frac{(1 - R^2)(n - 1)}{n - p - 1} \qquad (3.0.4)$$

C. ***Mean Square Error (MSE):*** The MSE is the average of the squared residuals:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \epsilon_i^2 = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \qquad (3.0.5)$$

In matrix notation, the residuals are represented as: $\epsilon = (y - X\hat{\beta})$. And the squared residuals are then: $\epsilon^2 = \epsilon^T \epsilon = (y - X\hat{\beta})^T (y - X\hat{\beta})$. Thus, the MSE can be expressed in matrix form as:

$$MSE = \frac{1}{n} (y - X\hat{\beta})^T (y - X\hat{\beta}) \qquad (3.0.6)$$

D. *Mean Absolute Error (MAE):* The average of the absolute residuals is given by

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\epsilon_i| = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| = \frac{1}{n}\sum_{i=1}^{n}\left|(y_i - X_i^T\beta)\right| \qquad (3.0.7)$$

For practical applications, the MSE is often preferred when large errors need to be penalized more heavily (e.g., in models where outliers are important). While the MAE is more robust to outliers and is often used when the focus is on median-like behaviour or when the distribution of residuals is not Gaussian.

3.5. Mathematical Concept of RRMs

The study uses RRMs principle to analyze the relationship between the key severity ratios of terrorism and the target variables. The RRM is chosen for its ability to handle high-dimensional data and provide robust estimates of the relationships between variables (Hastie et al., 2015). The RRMs techniques refer to a set of statistical methods used to enhance the predictive performance of regression models by preventing overfitting. These techniques achieve this by introducing a penalty term to the loss function, which discourages overly complex models that may fit the noise in the training data rather than the underlying patterns. The primary goals of RRMs techniques are to improve model generalization and interpretability, especially in scenarios where the number of predictors is large relative to the number of observations.

Key aspects of RRMs techniques underscored the control and management of model complexity by adding information that constrains the estimation process, thus addressing issues related to overfitting and multicollinearity. The mathematical concept underpinning RRT can be described through the modification of the standard linear regression loss function by adding a penalty term. Consider the OLS, the objective of standard linear regression is to minimize the residual sum of squares (RSS):

$$\text{Minimize } L(\beta) = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2 = \sum_{i=1}^{n}(y_i - X_i\beta)^2 \qquad (3.0.5)$$

Where: y_i is the observed response; $\hat{y}_i$ is the predicted response; X_i is the vector of predictors, and β is the vector of coefficients. Two prominent RRM techniques used in statistical modeling are the RRT and LRM model; particularly useful in high-dimensional datasets where the number of predictors exceeds the number of observations. These techniques are increasingly relevant in the field of terrorism modeling, where researchers aim to understand the complex interplay of various factors contributing to terrorist activities.

3.5.1. Ridge Regression (RRT):

RRT, also known as Tikhonov regularization applies an L2 penalty to the regression coefficients, which helps to mitigate issues of multicollinearity and overfitting. By adding a penalty proportional to the square of the coefficients, RRT shrinks the coefficients of less important predictors, allowing for all variables to remain in the model. This is particularly beneficial in terrorism studies, where numerous socio-economic, political, and historical factors may influence the likelihood of terrorist incidents. The ability to retain all predictors while controlling their impact enhances the robustness of the model (Hoerl, & Kennard, 1970). Mathematically, the RRT modifies the OLS objective by adding an L2 penalty term:

$$\text{Minimize } L(\beta) = \sum_{i=1}^{n}(y_i - X_i\beta)^2 + \lambda\sum_{j=1}^{p}\beta_j^2 \qquad (3.0.6)$$

Where, $\lambda \geq 0$ is the regularization parameter that controls the strength of the penalty, and p is the number of predictors.

3.5.2. Lasso Regression (LRM):

Lasso, or Least Absolute Shrinkage and Selection Operator, on the other hand, employs an L1 penalty, which not only shrinks coefficients but can also set some of them to zero. This feature selection capability makes LRT particularly valuable in terrorism modeling, where identifying the most significant predictors can lead to more interpretable and actionable insights. By focusing on a smaller subset of influential variables, researchers can better understand the key drivers of terrorism and inform policy decisions (Tibshirani, 1996; Hastie, et al., 2015). Mathematically, LRM modifies the OLS objective by adding an L1 penalty term:

$$\text{Minimize } L(\beta) = \sum_{i=1}^{n}(y_i - X_i\beta)^2 + \lambda\sum_{j=1}^{p}|\beta_j| \qquad (3.0.7)$$

Similar to Ridge, $\lambda \geq 0$ controls the strength of the penalty. In summary, both Ridge and LRM techniques enhance standard linear regression by incorporating regularization terms to the loss function, which helps prevent overfitting and improve model performance in high-dimensional datasets.

3.6. Mathematical Concept of ACTs:

The Anarchical coefficients of terrorism (ACTs) is a conceptual framework used to quantify and model the chaotic and unpredictable nature of terrorist activities within a geopolitical or socio-economic system. It is rooted in the intersection of statistical modeling, chaos theory, and criminology (Shannon, 1948; Sandler, & Enders, 2004; Mandelbrot, 1982; Porter, & White, 2012). This coefficient seeks to measure the degree of disorder or randomness in the frequency, intensity, and spatial distribution of terrorist events. By doing so, it provides policymakers, analysts, and researchers with a quantitative tool to assess the volatility of terrorism in a given region or time frame. To quantify the ACT for the Northern region, we integrate the multiple dimensions of terrorism data: frequency of incidents, number of casualties, number of cities affected, and number of perpetrator groups. The ACT is designed to measure the degree of disorder, unpredictability, and intensity of terrorism in the region. To develop the mathematical framework for calculating the ACT, let define the key variables:

- F: Frequency of terror incidents in the region (number of attacks over a specific time period, e.g., per year).
- C: Total number of casualties (sum of deaths and injuries) from all incidents in the region.
- N_c: Number of unique cities affected by terror incidents.
- N_p: Number of perpetrator groups involved in the incidents.
- T: Total time period under consideration (e.g., in years).
- A: Total area of the geopolitical region under consideration (e.g., in square kilometres)

Derived variables:

- $D_c = \frac{N_c}{A}$: City density of terrorism (number of affected cities per unit area).
- $F_r = \frac{F}{T}$: Frequency rate of terror incidents (average number of incidents per year).
- $C_r = \frac{C}{F}$: Casualty rate per incident (average number of casualties per attack).

The ACT constructed is a composite index that integrates frequency, intensity, spatial dispersion, and actor diversity. Each component is normalized to ensure comparability and weighted to reflect its contribution to the overall anarchy of terrorism.

A. **Frequency Component $(ACT)_F$:** The frequency component measures the unpredictability of the number of incidents over time, and modelled using the coefficient of variation (CV), which captures the dispersion of incidents relative to the mean:

$$(ACT)_F = \omega_F \frac{\sigma_F}{\mu_F} \tag{3.0.8}$$

Where, σ_F : Standard deviation of the number of incidents per year, μ_F: Mean number of incidents per year, and ω_F is the weights assigned to frequency component (e.g., based on expert judgment or equal weighting). A higher $(ACT)_F$ indicates greater variability in the frequency of attacks, reflecting more anarchy.

B. **Intensity Component $(ACT)_I$:** The intensity component measures the severity of attacks in terms of casualties. It is modelled using an entropy-based measure to capture the randomness in the distribution of casualties:

$$(ACT)_I = -\omega_I \sum_{i=1}^{F} p_i log(p_i) \tag{3.0.9}$$

Where: $p_i = \frac{C_i}{C}$: Proportion of total casualties caused by the i-th incident, and ω_I is the weights assigned to intensity component (e.g., based on expert judgment or equal weighting). A higher $(ACT)_I$ indicates a more uneven distribution of casualties, with some attacks causing disproportionately high damage.

C. **Spatial Dispersion Component (ACT)S:** The spatial component measures the geographic spread of terrorism across the region. It is modelled using the spatial entropy of affected cities:

$$(ACT)_S = \omega_S - \sum_{j=1}^{N_c} q_j log(q_j) \qquad (3.1.0)$$

Where, $q_j = \frac{1}{N_c}$: Probability of a city being affected (assumes uniform probability across all affected cities), and ω_S is the weights assigned to spatial dispersion component (e.g., based on expert judgment or equal weighting). A higher $(ACT)_S$ indicates a more dispersed pattern of attacks, reflecting greater geographic unpredictability.

D. **Actor Diversity Component (ACT)A*:*** The actor diversity component measures the number and diversity of perpetrator groups involved. It is modelled using the Shannon Diversity Index (Shannon, 1948):

$$(ACT)_A = -\omega_A \sum_{k=1}^{N_p} r_k log(r_k) \qquad (3.1.1)$$

Where, $r_k = \frac{F_k}{F}$ **:** Proportion of incidents attributed to the k-th perpetrator group, and ω_A is the weights assigned to actor diversity component (e.g., based on expert judgment or equal weighting). A higher $(ACT)_A$ indicates greater diversity in the actors involved, reflecting more organizational complexity.

E. **Composite Index for ACT:** The overall ACT is a weighted sum of the four components:

$$ACT = \frac{1}{N}\sum_{X=1}^{N}(ACT)_X = \frac{1}{N}[(ACT)_F + (ACT)_I + (ACT)_S + (ACT)_A] \qquad (3.1.2)$$

ACT - the final index value, represent the overall anarchical characteristics of the region, with respect to terrorism.

F. **Normalization of (ACT)X:** To ensure comparability across regions or time periods, each component is normalized to a scale of 0 to 1:

$$(ACT)_X = \frac{(ACT)_X - Min(ACT)_X}{Max(ACT)_X - Min(ACT)_X} \qquad (3.1.3)$$

Where $(ACT)_X$ represents any of the components $(ACT)_F, (ACT)_I, (ACT)_S, (ACT)_A$. For $(ACT) \to 0$ indicates low anarchy, with terrorism being highly predictable and localized, and $(ACT) \to 1$ indicates high anarchy, with terrorism being highly unpredictable, dispersed, and severe. In summary, this framework provides a robust and flexible approach to quantifying the anarchy of terrorism in a geopolitical region. Let me know if you'd like to explore practical examples or simulations using this model.

3.7. Model Specification:

The general structure of a multivariate regression model can be expressed as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \epsilon \qquad (3.1.4)$$

Where; Y is the dependent variable (number of incidents, number of perpetrator groups, number of cities affected, and number of casualties); β_0 is the intercept; β_i are the coefficients for the independent variables; X_i are the independent variables, (number of perpetrators per incident, number of casualties per incident, number of casualties per city, number of casualties per perpetrator's group, number of incidents per perpetrator's group, and number of incidents per city, and ϵ is the error term that cannot be explained by the model. Therefore, the models representing each of the dependent variables can be given by:

- *Terror Incidents:* $Y_1 = \beta_{10} + \beta_{11} X_1 + \beta_{12} X_2 + \beta_{13} X_3 + \beta_{14} X_4 + \beta_{15} X_5 + \beta_{16} X_6 + \epsilon_1$ (3.1.5)
- *Perpetrator Groups:* $Y_2 = \beta_{20} + \beta_{21} X_1 + \beta_{22} X_2 + \beta_{23} X_3 + \beta_{24} X_4 + \beta_{25} X_5 + \beta_{26} X_6 + \epsilon_2$ (3.1.6)
- *Cities Affected:* $Y_3 = \beta_{30} + \beta_{31} X_1 + \beta_{32} X_2 + \beta_{33} X_3 + \beta_{34} X_4 + \beta_{35} X_5 + \beta_{36} X_6 + \epsilon_3$ (3.1.7)

➢ *Casualties:* $Y_4 = \beta_{40} + \beta_{41}X_1 + \beta_{42}X_2 + \beta_{43}X_3 + \beta_{44}X_4 + \beta_{45}X_5 + \beta_{46}X_6 + \epsilon_4$ (3.1.8)

By combine Equations (3.1.5) to (3.1.8) in matrix form, we have

$$\begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \\ Y_4 \end{bmatrix} = \begin{bmatrix} \beta_{10} & \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} & \beta_{15} & \beta_{16} \\ \beta_{20} & \beta_{21} & \beta_{22} & \beta_{23} & \beta_{24} & \beta_{25} & \beta_{26} \\ \beta_{30} & \beta_{31} & \beta_{32} & \beta_{33} & \beta_{34} & \beta_{35} & \beta_{36} \\ \beta_{40} & \beta_{41} & \beta_{42} & \beta_{43} & \beta_{44} & \beta_{45} & \beta_{46} \end{bmatrix} \begin{bmatrix} 1 & X_1 & X_2 & X_3 & X_4 & X_5 & X_6 \\ 1 & X_1 & X_2 & X_3 & X_4 & X_5 & X_6 \\ 1 & X_1 & X_2 & X_3 & X_4 & X_5 & X_6 \\ 1 & X_1 & X_2 & X_3 & X_4 & X_5 & X_6 \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \epsilon_4 \end{bmatrix} \quad (3.1.9)$$

$$Y = \beta X + \epsilon$$

Where; Y_1 is the Number of Incidents; Y_2 is the Number of Perpetrator Groups; Y_3 is the Number of Cities Affected; Y_4 is the Number of Casualties; β_{i0} is the respective intercept of the equations; β_{ij} are the coefficients for the independent variables; X_1 is the Number of perpetrators per incident; X_2 is the Number of Casualties per incident; X_3 is Number of Casualties per city; X_4 is the Number of Casualties per perpetrator's group; X_5 is Number of Incidents per perpetrator's group; X_6 is the Number of Incidents per city, and, ϵ_i is the respective error term that cannot be explained by the model. Models (3.0.9 -3.1.2) were analyzed using Python codes implementation of LRT and RRT techniques, and the results discussed under relevant theoretics context.

3.8. Ethical Considerations:

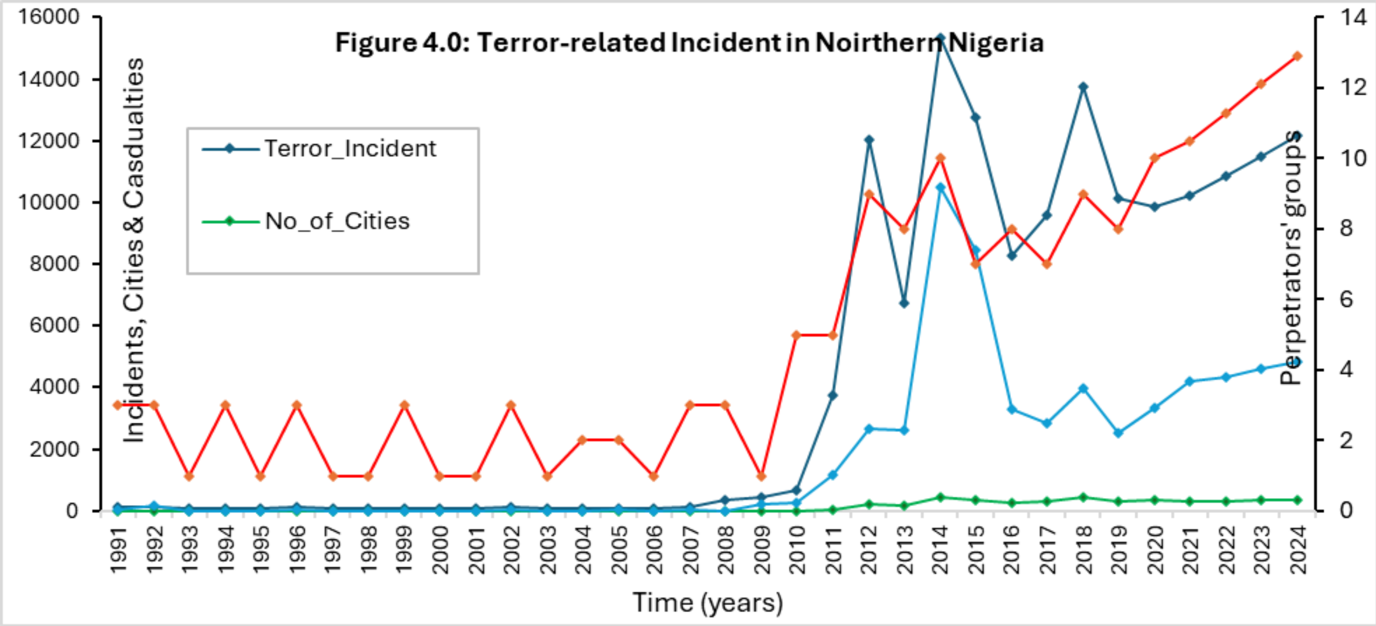
While this study provides valuable insights into the severity dynamics of terrorism, it is crucial to address the ethical considerations associated with the use of terrorism data. In conducting this study, we recognize the importance of ethical safeguards to ensure the responsible use of terrorism data. This includes:

1. **Data Privacy and Confidentiality**: We took great care to anonymize and de-identify any personal data related to victims or communities affected by terrorism. Our commitment to protecting individuals' privacy guided our data handling protocols, ensuring compliance with ethical standards and local regulations.
2. **Responsible Communication of Findings**: We are committed to communicating our findings thoughtfully and responsibly. We provided clear context and limitations in our research, emphasizing that our data should be used to inform constructive CT strategies rather than justifying any form of violence or discrimination.
3. **Engagement with Affected Communities**: We prioritized engaging with communities affected by terrorism throughout our research process. By conducting consultations and involving local stakeholders, we ensured that their perspectives were considered, and we aimed to create a research outcome that genuinely benefits those impacted by violence.
4. **Transparency and Accountability**: We maintained transparency about our research methods, data sources, and potential conflicts of interest. Our methodology section includes a detailed account of how we collected, analyzed, and interpreted the data, reflecting our commitment to accountability.
5. **Ethical Review Processes**: Before commencing our research, we sought approval from relevant authorities to ensure that all ethical considerations were addressed. This step reinforced our dedication to conducting research that adheres to the highest ethical standards.

By adhering to these strict personalized ethical safeguards, we aimed to enhance the credibility of our study while promoting the responsible use of terrorism data. Our commitment to ethical considerations not only strengthens our research but also contributes to a more informed and constructive discourse on CT strategies, minimizing the risk of harm to individuals and communities affected by violence.

4. MODEL ANALYSIS

To achieve the study, aim and objective, the study explores and collated Northern Nigerian terrormographics dataset from 1991 – 2024. This data consists of date of incident, number of Terror incidents, number of cities affected, number casualties, and number of perpetrators groups. These data were collated, pre-processed and preliminary analysis was carried out to evaluate the relevant predictor variable - severity ratios, necessary for the respective RRMs analysis. Figure 4.0 and 4.1, represent the respective visualization of the research dataset.



The Figure 4.0 above, track the trends in terror-related incidents in Northern Nigeria, from 1991 to 2024, this includes:

1. **Incidents:** The number of terror incidents shows a significant increase starting around 2010, peaking around 2015, and then decreasing but remaining at a higher level than pre-2010 era.
2. **Cities Affected:** The number of cities affected remains comparatively low and stable throughout the period.
3. **Casualties:** Casualties follow the trend of terror incidents, with a notable spike around 2013-2015.
4. **Perpetrators' Groups:** The number of perpetrator groups appears relatively stable until 2010, after which it steadily increases.

Figure 4.1 above, track the trends of various ratios of terrorism severity over time, from 1991 to 2024 in Northern Nigeria. Demonstrating that the severity trends were generally low between 1991-2007, indicating a period of relatively low severity. 2008-2016 saw a significant increases in several ratios, particularly Casualty per Perpetrator (*black curve*), Incident per Perpetrator *(yellow curve)*, and Casualty per Incident (*pink curve*). This suggests a period of heightened severity, with attacks becoming more lethal and impactful. However, the post-2016 trends indicate a decline in Incident per Perpetrator *(yellow curve)* but stabilization or slight increase in casualty per City *(red curve)*. This could indicate a shift in tactics or targets, with a focus on causing more concentrated harm in specific areas.

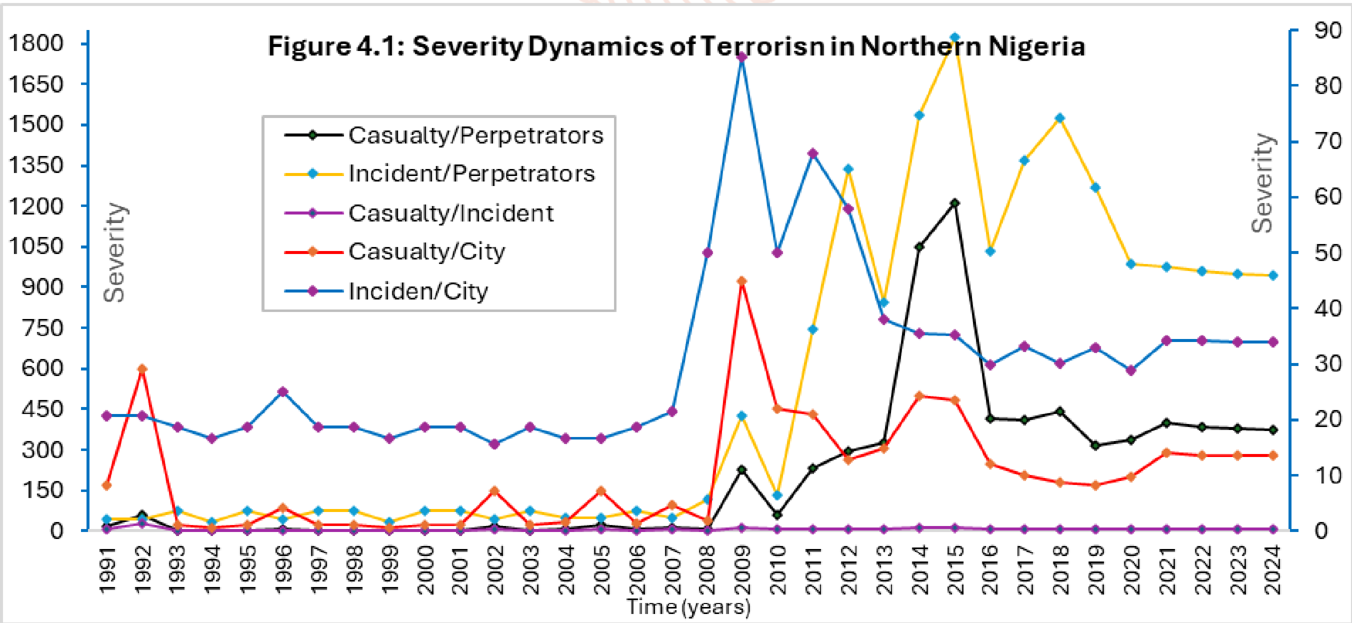
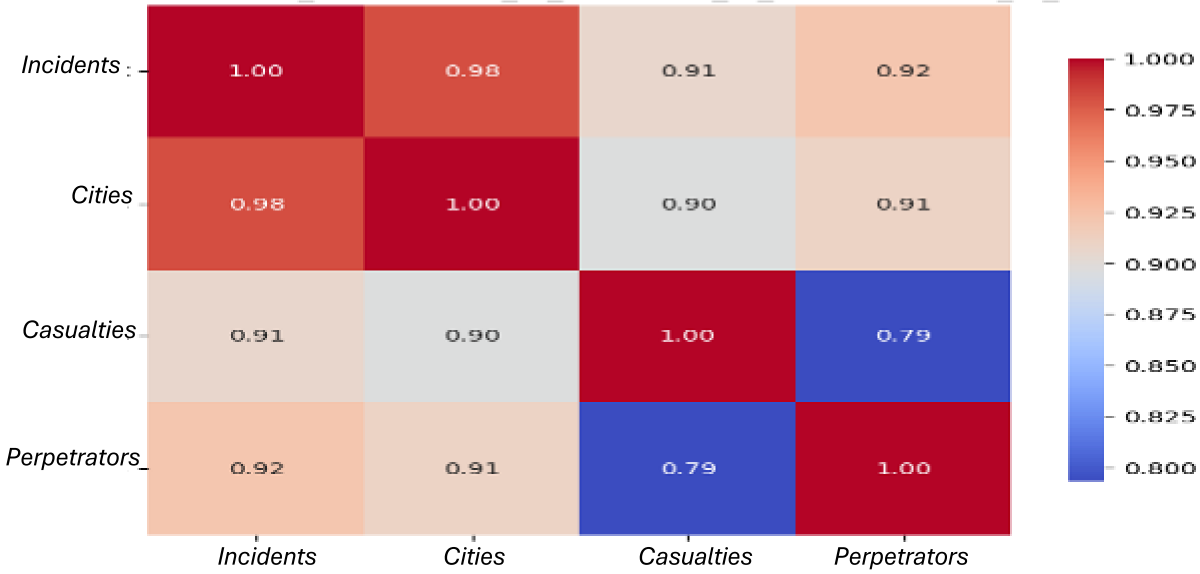


Figure 4.2: Correlation Between the Target Variables



The Figure 4.2 above track significant correlation between the target variables. Summarily, the correlation matrix displays strong relationships among the variables related to incidents, casualties, and perpetrators' groups in the context of terrorism severity dynamics.

1. **Incidents and Cities Affected (0.98):** Is an exceptionally high positive correlation, indicating that as the number of incidents increases, the number of cities affected almost perfectly aligns, suggesting that more frequent attacks tend to target a wider geographical area.
2. **Incidents and Casualties (0.91):** Is a very strong positive correlation, suggesting that an increase in the number of incidents is associated with a significant rise in casualties, highlighting the lethal impact of frequent attacks.
3. **Incidents and Perpetrators' Group (0.92):** Is also a very strong positive correlation - suggesting that more incidents are likely to be executed by a greater number of perpetrators' groups, indicating a relationship between the frequency of attacks and the diversity of groups involved.
4. **City Affected and Casualties (0.90):** Is a strong positive correlation - indicating that cities experiencing more incidents also tend to have higher casualties, emphasizing the relationship between urban violence and its impact on populations. The correlation between the
5. **City Affected and Perpetrators' Groups (0.91):** Is also a strong positive correlation - suggests that cities with more incidents are likely to be targeted by a greater number of different perpetrator groups, reflecting the complexity of urban terrorism dynamics.
6. **Casualties and Perpetrators' Groups (0.79):** This strong positive correlation suggests that cities with higher casualty counts may be associated with a greater diversity of perpetrator groups, indicating a link between lethality and group complexity.

In conclusion, the correlations matrix highlights a robust relationship between incidents, casualties, and the diversity of perpetrator groups. The extremely high correlations between the number of incidents and cities affected suggest that terrorism in this context is both frequent and widespread. These findings emphasize the need for comprehensive CT strategies that consider the intricate relationships among these factors to effectively address the challenges posed by terrorist activities.

Figure 4.3: Correlation between the Predictor Variables

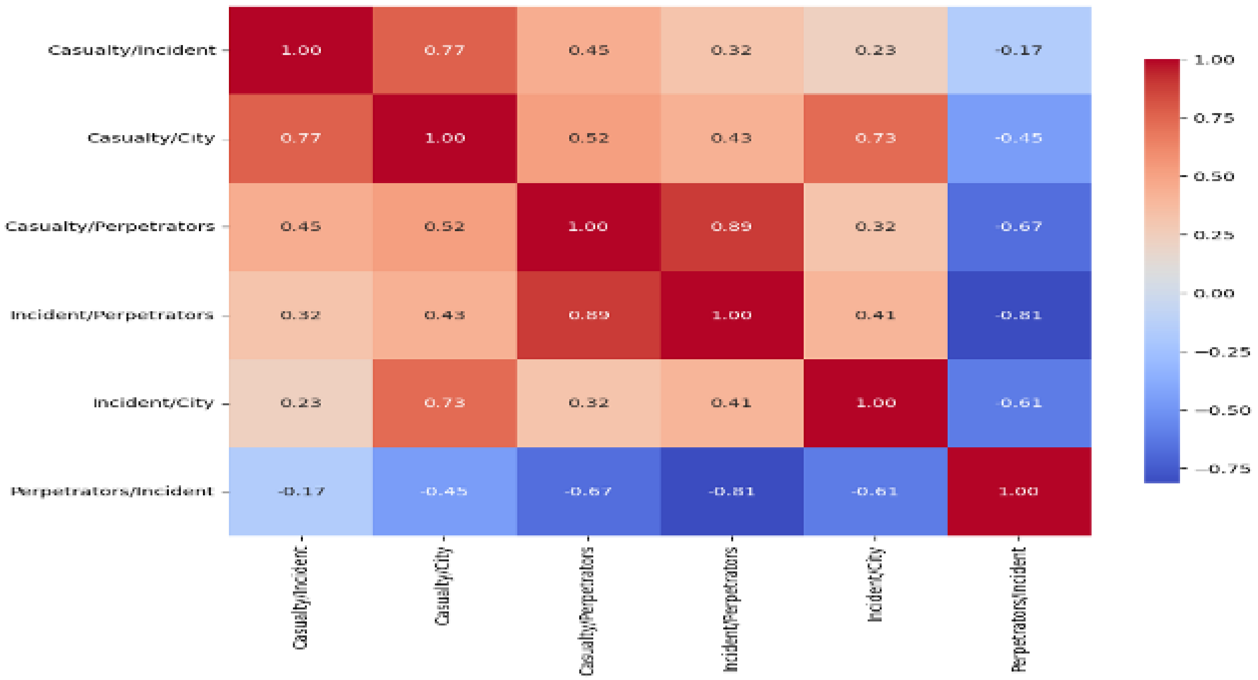


Figure 4.3 above tracks the correlation between the predictor variables – the respective severity ratios. Summarily, the correlation matrix reveals several key relationships among the variables related to terrorism dynamics, specifically focusing on casualties, incidents, and perpetrators.

1. **Casualty/Incident and Casualty/City (0.77)**: Is a strong positive correlation - suggests that as the average casualties per incident increase, the average casualties per city also tend to rise, indicating that more lethal attacks significantly impact urban areas.
2. **Casualty/Perpetrator and Incident/Perpetrators (0.89)**: Is a very strong positive correlation - suggesting that groups causing higher casualties are also more likely to execute multiple incidents, reflecting the operational capacity of lethal groups.
3. **Casualty/City and Incident/City (0.73)**: Is a moderate positive correlation - indicating that cities with higher average casualties also tend to experience more incidents, suggesting a relationship between severity and frequency of attacks in urban settings.
4. **Casualty/City and Casualty/Perpetrators (0.52)**: Is a moderate positive correlation implies that cities with higher casualties are also associated with more casualties attributed to individual perpetrators, highlighting the severity of attacks.
5. **Casualty/Incident and Casualty/Perpetrator (0.45):** Is a weaker positive correlation - suggests a relationship between the number of casualties per incident and the average casualties per perpetrator, indicating that more lethal incidents may involve more lethal groups.
6. **Incident/Perpetrators and Incident/City (0.41)**: Is also a weak positive correlation - suggesting that as the number of incidents per perpetrator increases, the overall number of incidents in cities also rises.
7. **Casualty/Incident and Perpetrators/Incident (-0.17)**: Indicate a slight negative correlation - suggesting that as the number of perpetrators involved in incidents increases, the average casualties per incident may decrease, indicating that larger groups could be less lethal on a per-capita basis.
8. **Perpetrators/Incident and Incident/City (-0.61)**: Indicate a significant negative correlation - suggests that larger groups may be associated with fewer incidents per city, indicating that concentrated efforts by these groups could lead to high-impact attacks but fewer overall incidents.

In conclusion, the correlations highlight the complex interplay between casualties, incidents, and perpetrators in the context of terrorism. Strong positive correlations emphasize the need for targeted interventions in high-casualty areas, while negative correlations suggest that larger groups may operate differently, potentially leading to fewer incidents but with greater impact. Understanding these relationships is crucial for developing effective CT strategies.

4.1. Model Evaluation and Validation

Prior to the evaluation of the respective coefficients (β_i) of models (3.0.9- 3.1.2), and hence, fit each model to the research dataset, we first carry out the relevant data validity tests on the predictor variables - multicollinearity, autocorrelation and normality tests, using the OLS principle. This enables us understand their characteristics, and hence, justify our choice for RRMs techniques. The study uses various evaluation metrics, including the Omnibus Test, Jarque-Bera (JB), Durbin-Watson, and the Condition Number tests, to evaluate these characteristics, and the performance of the model (Gujarati, & Porter, 2009). From python implementation of OLS analysis:

- **Omnibus Test (3.164) and Prob (Omnibus) (0.206):** The Omnibus test and its p-value – Prob (Omnibus) test for the normality of the model's residuals. The Omnibus Test value of 3.164 and its p-value of 0.206, greater than 0.05, suggest that, the residuals are normally distributed.
- **Jarque-Bera (JB) Test (1.851) and Prob (JB) (0.396):** This test assesses the normality of the residuals based on skewness and kurtosis. The JB statistic evaluates whether the data deviates from a normal distribution. With JB value of 1.851 and its p-value of 0.396, greater than 0.05, confirm that the residuals show no significant deviation from normality.
- **Durbin-Watson Test (1.315):** The Durbin-Watson statistic tests for autocorrelation in the residuals. A value of 1.315 suggests some positive autocorrelation in the residuals, which could be a concern for our model's validity.
- **Condition Number (1.85e+05):** The condition number assesses multicollinearity. A value of 1.85e+05 suggests severe multicollinearity, which can affect the stability and interpretability of the regression coefficients.

These results justify our choice for RRMs techniques, which help mitigate the effects of multicollinearity and autocorrelation by applying penalties to the size of coefficients.

4.2. Severity by Terror Incidents

From Python implementation of LRM analysis, the results of analysis of model (3.0.9) yield the following metrics:

- ***R^2 (R Square) value of 0.7597:*** This indicates how well our model explains the variability of the outcome. An R^2 of 0.7597 means our model explains 75.97% of the changes in the severity of terrorism with respect to the number of Incidents
- ***Mean Squared Error (MSE) (8.46):*** This measures the average squared difference between predicted and actual values. A lower MSE indicates better model accuracy. The relatively small average error (8.46), indicate a better model accuracy.
- ***Coefficient (β_{ij}):*** This indicates the correlation between the predictor's variables and terror incident. The LRM analysis yields approximately: 594.52, -781.52, 829.32, 4135.33, -505.02, and -400.88. By substituting these coefficient values into model (3.0.4), we have:

$$\begin{aligned} Y_1 &= \beta_{10} + \beta_{11}X_1 + \beta_{12}X_2 + \beta_{13}X_3 + \beta_{14}X_4 + \beta_{15}X_5 + \beta_{16}X_6 + \epsilon_1 \\ &= 594.52X_1 - 781.52X_2 + 829.32X_3 + 4135.33X_4 - 505.02X_5 - 400.88X_6 \end{aligned} \tag{4.0.0}$$

By the equation (4.0.0), given a unit change in all predictor variables, then the number of terror incident will increase by approximately: $Y_1 \approx 3{,}872$.

4.2.1. Interpretation of Model 4.0.0 Coefficients (β_{1j}): The model coefficients (β_{1j}) represent the relationship between each independent variable and the dependent variable (terror incident), and hence, the estimated change in the dependent variable for a one-unit change in the respective predictor, holding all other variables constant. Positive coefficients indicate a direct relationship, while negative coefficients suggest an inverse relationship.

1. **Casualty per Incident (β_{11}=594.52):** This indicates that for every 1-unit increase in casualties per incident, the total number of future terror incidents is expected to increase by 595, holding other variables constant. This suggests that high-casualty incidents may lead to an escalation in subsequent attacks. Theoretically, this aligns with the Contagion Theory (Myers, 2000), which posits that violent events, such as high-casualty

terror incidents, can inspire imitation or retaliation. A high-casualty event may amplify media attention, provoke fear, and embolden other perpetrators to act, leading to an increase in subsequent incidents. Cycle of Violence Theory (Gilligan, 1996; LaFree et al., 2015), also emphasized that high-casualty incidents may perpetuate a cycle of violence, where one violent act triggers retaliatory actions. Terrorist groups may exploit high-casualty incidents to amplify fear and destabilize governance. This implies that incident with higher casualties is likely to trigger more future incidents. This highlights the need for targeted interventions to break the cycle of violence and prevent escalation.

2. **Casualty per City (β_{12}=-781.52):** This indicates that for every 1-unit increase in casualties per city, the number of future terror incidents is expected to decrease by 782, holding other variables constant. This could indicate that cities experiencing high casualties may implement stricter security measures or experience reduced activity due to the severity of prior attacks. Theoretically, this result aligns with the Rational Choice Theory (Cornish & Clarke, 1986), which observed that terrorists are rational actors who assess the risks and benefits of their actions. High-casualty incidents in a city may lead to increased security measures, making it a less attractive target for future attacks. This aligns with the idea that offenders adapt their behaviour based on environmental changes. The Deterrence Theory (Beccaria, 1764), also observed that High-casualty events often trigger heightened law enforcement and surveillance, which act as deterrents to future attacks. The negative coefficient reflects this deterrence effect.

3. **Casualty per Perpetrators (β_{13}=829.32):** This implies that for every 1-unit increase in casualties per perpetrator, the number of future terror incidents is expected to increase by 829, holding other variables constant. This suggests that more lethal perpetrators or groups are associated with higher incident frequencies. Theoretically, this result aligns with the Capability Theory (McCarthy & Zald, 1977), which suggests that the operational capacity of terrorist perpetrators (e.g., access to weapons, training, and resources) influences their ability to cause harm. Higher casualties per perpetrator may reflect greater capability, which correlates with an increased frequency of incidents. The Routine Activity Theory (Cohen & Felson, 1979), also observed that perpetrators' group who are capable of causing high casualties are likely to have access to suitable targets and a lack of capable guardians, increasing the likelihood of repeated attacks.

4. **Incident per Perpetrators (β_{14}=4135.33):** This indicate that for every 1-unit increase in incident per perpetrator, the total number of future terror incidents is expected to increase by 4135, holding other variables constant. This highlights the role of organized groups or individuals capable of executing multiple attacks. Theoretically, this aligns with the Social Network Theory (Granovetter, 1973), which observed that terrorist organizations often operate as networks with shared resources and coordinated strategies. A high number of incidents per perpetrator reflect the efficiency and coordination of such networks. The Organizational Dynamics Theory (Crenshaw, 1985), emphasizes the role of organizational structure in terrorism. Groups with centralized leadership and clear objectives are more likely to execute multiple attacks, as reflected by the positive coefficient.

5. **Incident per City (β_{15}-505.02):** This indicates that for every 1-unit increase in incident per city, the total number of terror incidents is expected to decrease by 505, holding other variables constant. This may be due to most terrorist organizations' concentrated efforts in specific cities, leading to a decline in overall incidents. Theoretically, this aligns with the Broken Windows Theory (Wilson & Kelling, 1982). This theory suggests that visible signs of disorder (e.g., frequent incidents in a city) prompt authorities to take action to restore order. Increased law enforcement and community engagement in high-incident cities may reduce overall incidents. The Opportunity Theory (Clarke, 1983) observed that terrorists often exploit opportunities for attacks. A high number of incidents in a city may lead to reduced opportunities elsewhere, as resources are concentrated in high-risk areas.

6. **Perpetrators per Incident (β_{15}=-400.88):** This indicates that for every 1-unit increase in perpetrator per incident, the total number of terror incidents is expected to decrease by 401, holding other variables constant. This indicate that larger groups are less frequent but more impactful, leading to fewer overall incidents. By Economies of Scale in Terrorism (Enders & Sandler, 2006), larger groups often plan fewer but more impactful attacks due to the complexity of coordination and resource allocation. The negative coefficient reflects this trade-off between group size and frequency of incidents. The Collective Action Theory (Olson, 1965), also observed that larger groups face challenges in maintaining cohesion and coordination, which may limit their ability to execute frequent attacks. This aligns with the observed negative relationship.

In conclusion, each coefficient model (4.0.0) aligns with established theories in criminology, sociology, and terrorism studies. By integrating these theories, we gain a deeper understanding of the dynamics driving terror incidents and their relationship with key variables. This theoretical grounding enhances the practical utility of the analysis for policymakers and security agencies

4.2.2. Implications of Incident Severity

1. **Resource Allocation:** The strong positive relationship between Incident per Perpetrators and terror incidents suggests that security forces should prioritize monitoring and disrupting organized groups capable of executing multiple attacks. Intelligence efforts should focus on identifying networks and their operational capacities.
2. **Targeted Interventions:** The negative coefficient for Casualty per City implies that cities with higher casualties may benefit from enhanced security measures. Policymakers should consider deploying additional resources to such areas to prevent further incidents.
3. **Prevention Strategies:** The positive coefficient for Casualty per Incident highlights the importance of preventing high-casualty events, as they may lead to a cycle of retaliatory violence. Strategies should include community engagement and conflict resolution to address underlying grievances.
4. **Monitoring High-Risk Areas:** The large positive coefficient for Incident per Perpetrator underscores the need to monitor regions with high incident-perpetrator ratios. These areas may serve as hubs for planning and executing attacks.
5. **Disruption of Networks:** The negative coefficient for Perpetrator per Incident suggests that larger groups may execute fewer incidents but with greater impact. Security agencies should focus on dismantling such groups to reduce their operational capacity.
6. **Policy Implications:** Governments should consider implementing policies that address the root causes of terrorism, such as socioeconomic disparities and political grievances. The relationships between variables like Casualty per City and Incident per City highlight the importance of addressing structural factors that contribute to violence.

4.3. Severity by Perpetrator's Group:

From Python implementation of RRT analysis, the results of analysis of model (3.1.0) yield the following metrics:

- ***R^2 (R Square) value of 0.847:*** This indicates how well our model explains the variability of the outcome. An R^2 of 0.847 means our model explains 75.97% of the changes in the severity of terrorism with respect to the number of Incidents
- ***Mean Squared Error (MSE) (5.97):*** This measures the average squared difference between predicted and actual values. A lower MSE indicates better model accuracy. The relatively small average error (5.97), indicate a better model accuracy.
- ***Coefficient (β_{ij}):*** This indicates the correlation between the predictor's variables and terror incident. RRT analysis yields approximately: 1.18, -1.24, 0.09, 3.23, 0.05, and -0.32. Substituting these coefficient values into model (3.1.0), yield:

$$\begin{aligned} Y_2 &= \beta_{20} + \beta_{21}X_1 + \beta_{22}X_2 + \beta_{23}X_3 + \beta_{24}X_4 + \beta_{25}X_5 + \beta_{26}X_6 + \epsilon_2 \\ &= 1.18X_1 - 1.24X_2 + 0.09X_3 + 3.23X_4 + 0.05X_5 - 0.32X_6 \end{aligned} \qquad (4.0.1)$$

By the equation (4.0.1), given a unit change in all predictor variables, then the number of perpetrator's group will increase by approximately, $Y_2 \approx 3$.

4.3.1. Interpretation of model 4.0.1 Coefficient (β_{2j}): The model coefficients β_{2j} represent the relationship between each independent variable and the dependent variable (perpetrator's groups), and hence, the estimated change in the dependent variable for a one-unit change in the respective predictor, holding all other variables constant. Positive coefficients indicate a direct relationship, while negative coefficients suggest an inverse relationship.

1. **Casualty per Incident (β_{21}=1.18):** The indicates that for every 1-unit increase in casualty per incident, the total number of perpetrator's group is expected to increase by 1.18, holding other variables constant. This suggests that high-casualty incidents may attract or involve more organized groups. Theoretically, this aligns

with the Competition Theory (Bloom, 2005) which observed that terrorist organizations often compete for influence, resources, and public attention. High-casualty incidents may signal success, attracting more groups to participate in similar activities to gain notoriety or legitimacy. The Social Amplification of Risk Theory (Kasperson et al., 1988), emphasized that high-casualty incidents amplify public fear and media attention, creating an environment where more groups may emerge or align themselves with existing perpetrators to capitalize on the heightened visibility.

2. **Casualty per City (β_{22}=-1.24):** The indicates that for every 1-unit increase in casualty per city, the total number of perpetrator's group is expected to decrease by 1.24, holding other variables constant**.** This indicate that cities with high casualties are dominated by a few powerful groups, leaving little room for new entrants. Theoretically, this result aligns with the Monopoly of Violence Theory (Weber, 1946) which observed that in regions with high casualties, dominant groups may consolidate power, reducing the presence or emergence of competing groups. The Rational Choice Theory (Cornish & Clarke, 1986) also observed that perpetrator's groups may avoid cities with high casualties due to increased law enforcement and security measures, which raise the risks of operating in such areas.
3. **Casualty per Perpetrators (β_{23}=0.09):** The indicates that for every small increase in casualty per perpetrators, the total number of perpetrator's group is expected to increase slightly by 0.09, holding other variables constant**.** This indicate that more lethal perpetrators are associated with the emergence of additional groups. Theoretically, this aligns with the Capability Theory (McCarthy & Zald, 1977). This theory observed that higher lethality per perpetrator may reflect increased operational capacity, which could inspire splinter groups or new organizations to form, seeking to emulate or compete with the original group. The Franchise Model of Terrorism (Sageman, 2008) emphasized that lethal groups often serve as models for others, leading to the proliferation of smaller, ideologically aligned groups that replicate their tactics.
4. **Incident per Perpetrators (β_{24}=3.23):** The indicates that for every 1-unit increase in incident per perpetrators, the total number of perpetrator's group is expected to increase by 3.23, holding other variables constant**.** This suggests that frequent attacks by individual perpetrators or small groups may encourage the formation of additional groups. Theoretically, this result aligns with the Diffusion of Innovation Theory (Rogers, 1962) which observed that frequent terror incidents signal the success of certain tactics or strategies, encouraging other groups to adopt similar approaches, leading to an increase in the number of perpetrator groups. By Organizational Dynamics Theory (Crenshaw, 1985), frequent terror incidents may reflect the operational success of certain groups, inspiring fragmentation or the creation of splinter groups that replicate these tactics.
5. **Incident per City (β_{25}=0.05):** The indicates that for every small increase in incident per city, the total number of perpetrator's group is expected to increase slightly by 0.09, holding other variables constant**.** This indicate that cities with frequent incidents provide fertile ground for the emergence of new groups. Theoretically, this aligns with the Opportunity Theory (Clarke, 1983), which observed that cities with frequent incidents may present more opportunities for new groups to emerge, as they can exploit the existing instability and lack of capable guardians. By Social Disorganization Theory (Shaw & McKay, 1942), frequent terror incidents may reflect weak social structures and governance, creating an environment conducive to the formation of new perpetrator groups.
6. **Perpetrators per Incident *(β_{26}=-0.32):*** The indicates that for every small increase in perpetrators per incident, the total number of perpetrator's group is expected to decrease slightly by 0.32, holding other variables constant**.** This suggests that larger groups are more likely to dominate, reducing the overall number of groups. Theoretically, by the Economies of Scale in Terrorism (Enders & Sandler, 2006) larger terrorist groups often monopolize resources and operational capacity, leaving little room for smaller groups to emerge or operate, which aligns with the negative relationship. The Collective Action Theory (Olson, 1965) observed that larger terrorist groups are more cohesive and efficient, reducing the need for multiple small groups to operate in the same area. Inconclusion, the relationships observed in model (4.0.1.), highlight the importance of situational factors in preventing the emergence of new perpetrator groups.

4.3.2. Implications of Severity by Perpetrator's Group

1. **Monitoring High-Casualty Incidents:** The positive relationship between Casualty/Incident and perpetrator groups suggests that high-casualty incidents may attract new groups. Security agencies should focus on preventing such incidents and closely monitor areas where they occur to identify emerging groups.

2. **Targeting Dominant Groups in High-Casualty Cities:** The negative relationship between Casualty per City and perpetrator groups indicates that dominant groups may consolidate power in high-casualty cities. CT efforts should prioritize dismantling these dominant groups to prevent further violence.
3. **Disrupting Frequent Attackers:** The strong positive relationship between Incident per Perpetrator and perpetrator groups highlights the importance of disrupting individuals or small groups capable of frequent attacks. Early intervention can prevent the proliferation of new groups.
4. **Strengthening Urban Security:** The small positive relationship between Incident per City and perpetrator groups suggests that cities with frequent incidents are at risk of becoming hubs for new groups. Enhanced security measures and community engagement in such cities can help mitigate this risk.
5. **Preventing Group Fragmentation:** The positive relationship between Casualty per perpetrators and perpetrator groups suggests that lethal groups may inspire splintering or the formation of new groups. Efforts to address internal divisions within groups and reduce their operational capacity can limit fragmentation.
6. **Resource Allocation:** The negative relationship between Perpetrators per Incident and perpetrator groups indicates that larger groups are more likely to dominate. CT resources should focus on disrupting these larger groups to prevent them from monopolizing violence.

In conclusion, the result of analysis of model (4.0.1) results provide valuable insights into the factors influencing the emergence and proliferation of perpetrator groups. By grounding these findings in relevant theories, we can better understand the dynamics at play and develop targeted strategies to prevent and mitigate terrorism. Policymakers and security agencies should leverage these insights to allocate resources effectively and address the root causes of group formation.

4.4. Severity by Cities Affected:

By Python implementation of RRT technique, the results of analysis of model (3.1.1) yield the following metrics:

- **R^2 (R Square) value of 0.7267:** This indicates how well our model explains the variability of the outcome. An R^2 of 0.7261 means our model explains 72.61% of the changes in the severity of terrorism with respect to the number of Incidents
- **Mean Squared Error (MSE) (8.26):** This measures the average squared difference between predicted and actual values. A lower MSE indicates better model accuracy. The relatively small average error (8.26), indicate a better model accuracy.
- **Coefficient (β_{ij}):** This indicates the correlation between the predictor's variables and terror incident. The LRM analysis yields approximately: 16.13, -16.72, 31.74, 101.45, -29.29, and -27.25. Substituting these coefficient values into model (3.1.1), yield

$$\begin{aligned} Y_3 &= \beta_{30} + \beta_{31}X_1 + \beta_{32}X_2 + \beta_{33}X_3 + \beta_{34}X_4 + \beta_{35}X_5 + \beta_{36}X_6 + \epsilon_3 \\ &= 16.13X_1 - 16.72X_2 + 31.74X_3 + 101.45X_4 - 29.29X_5 - 27.252X_6 \end{aligned} \qquad (4.0.2)$$

By the equation (4.0.2), given a unit change in all predictor variables, then the number of cities affected will increase by approximately: $Y_3 \approx 76$.

4.4.1. Interpretation of Model 4.0.2 Coefficients (β_{3j}):

The model coefficients (β_{3j}) represent the relationship between each independent variable and the dependent variable (cities affected), and hence, the estimated change in the dependent variable for a one-unit change in the respective predictor, holding all other variables constant. Positive coefficients indicate a direct relationship, while negative coefficients suggest an inverse relationship.

1. **Casualty per Incident (β_{31}=16.13):** The indicates that for every 1-unit increase in casualty per incident, the total number of cities affected is expected to increase by 16.13 holding other variables constant. This suggests that high-casualty incidents may lead to the geographical spread of terrorism. Theoretically, this result aligns with the Contagion Theory (Myers, 2000) which opined that high-casualty incidents often generate significant media attention and public fear, which can inspire imitation or retaliation in other cities. By Social Amplification of Risk Theory (Kasperson et al., 1988), high-casualty events often amplify the perception of risk, potentially encouraging other groups to replicate such incidents in new locations to maximize their impact.

2. **Casualty per City (β_{32}=-16.72):** The indicates that for every 1-unit increase in casualty per city, the total number of cities affected is expected to decrease by 17, holding other variables constant. This indicate that high-casualty cities become focal points for terrorism, reducing the geographical spread. Theoretically, this aligns with the Monopoly of Violence Theory (Weber, 1946), which observed that in cities with high casualties, dominant groups may consolidate their operations, reducing the likelihood of attacks spreading to other cities. According to the Rational Choice Theory (Cornish & Clarke, 1986), terror perpetrators may focus their efforts on cities with high casualties to maximize their impact, rather than dispersing their activities across multiple locations.

3. **Casualty per Perpetrator (β_{33}= 31.74):** This indicates that for every 1-unit increase in casualty per perpetrators, the total number of cities affected is expected to increase by 32, holding other variables constant. This indicates that more lethal perpetrators or groups are associated with a wider geographical spread. Theoretically, this aligns with the Capability Theory (McCarthy & Zald, 1977) which opined that perpetrators with higher lethality often have greater operational capacity, enabling them to extend their activities to multiple cities. By Franchise Model of Terrorism (Sageman, 2008), lethal groups may inspire the formation of smaller, ideologically aligned groups in other cities, contributing to the geographical spread of terrorism.

4. **Incident per Perpetrators (β_{34}=101.45):** The implies that for every 1-unit increase in incident per perpetrators, the total number of cities affected is expected to increase by 101, holding other variables constant**.** This suggests that frequent of attacks by individual perpetrators or small groups are associated with a wider geographical spread. Theoretically, this aligns with the Diffusion of Innovation Theory (Rogers, 1962), which observed that frequent terror incidents signal the operational success of certain tactics, encouraging their adoption in new cities, thereby increasing the geographical spread. The Organizational Dynamics Theory (Crenshaw, 1985), also observed that frequent terror incidents may reflect the operational efficiency of certain groups, enabling them to expand their activities to multiple cities.

5. **Incident per City (β_{35}=-29.29):** The implies that for every 1-unit increase in incident per city, the total number of cities affected is expected to decrease by 29, holding other variables constant**.** This indicates that concentrated activity in specific cities limits the spread of terrorism to other locations. Theoretically, this also aligns with the Broken Windows Theory (Wilson & Kelling, 1982). By this theory, concentrated incidents in a city often prompt law enforcement and community engagement, reducing the likelihood of attacks spreading to other cities. By the Opportunity Theory (Clarke, 1983), perpetrators may focus their efforts on cities with frequent incidents due to the availability of opportunities, reducing the need to expand to other locations.

6. **Perpetrators per Incident (β_{36}=-27.25):** This implies that for every 1-unit increase in perpetrators per incident, the total number of cities affected is expected to decrease by 27, holding other variables constant**.** This suggests that larger groups are more likely to focus their activities in fewer cities, limiting the geographical spread**.** Theoretically, this aligns with the Economies of Scale in Terrorism (Enders & Sandler, 2006). By this theory, larger groups often centralize their operations in specific cities to maximize efficiency, reducing the geographical spread of their activities. The Collective Action Theory (Olson, 1965), observed that larger groups often face challenges in coordinating activities across multiple locations, leading to a concentration of efforts in fewer cities. In conclusion, the relationships observed in model (4.0.2.) highlight the importance of situational factors in preventing the geographical spread of terrorism.

4.4.2. Security Implications of Severity by City

1. **Preventing High-Casualty Incidents:** The positive relationship between Casualty per Incident and the number of cities affected suggests that high-casualty incidents may lead to the geographical spread of terrorism. Security agencies should prioritize preventing such incidents to limit their cascading effects.

2. **Focusing on High-Casualty Cities:** The negative relationship between Casualty per City and the number of cities affected indicates that high-casualty cities may act as focal points for terrorism. CT efforts should focus on these cities to prevent further escalation and contain the spread**.**

3. **Monitoring Lethal Perpetrators:** The positive relationship between Casualty per Perpetrator and the number of cities affected highlights the importance of monitoring and disrupting lethal perpetrators or groups. Early intervention can prevent the geographical spread of their activities.

4. **Disrupting Frequent Attackers:** The strong positive relationship between Incident/Perpetrators and the number of cities affected underscores the need to disrupt individuals or groups capable of frequent attacks. This can help limit the spread of terrorism to new cities.
5. **Strengthening Urban Security:** The negative relationship between Incident per City and the number of cities affected suggests that concentrated activity in specific cities may limit the spread of terrorism. Enhanced security measures and community engagement in high-incident cities can help contain the threat.
6. **Targeting Large Groups:** The negative relationship between Perpetrators/Incident and the number of cities affected indicates that larger groups are more likely to focus their activities in fewer cities. CT efforts should prioritize dismantling these groups to prevent concentrated attacks.

In conclusion, the results analysis of model (4.0.2) provides valuable insights into the factors influencing the geographical spread of terrorism. By grounding these findings in relevant theories, we can better understand the dynamics at play and develop targeted strategies to prevent and mitigate the spread of terrorism. Policymakers and security agencies should leverage these insights to allocate resources effectively and address the root causes of terrorism.

4.5. Severity by Casualties:

By Python implementation, the LRM analysis of model (3.1.2) yield the following metrics:

- ***R^2 (R Square) value (0.6742):*** *This indicates how well our model explains the variability of the outcome. An R^2 of 0.6742 means our model explains 67.42% of the changes in the severity of terrorism with respect to the number of Incidents*
- ***Mean Squared Error (MSE) (2.57):*** *This measures the average squared difference between predicted and actual values. A lower MSE indicates better model accuracy. The relatively small average error (2.57), indicate a better model accuracy.*
- ***Coefficient (β_{ij}):*** *This in*dicates the correlation between the predictor's variables and terror incident. The LRM analysis yields approximately: 272.84, -579.53, 2681.08, -202.81, -87.7, and -165.82. Substituting these coefficient values into model (3.1.2), yield:

$$\begin{aligned} Y_4 &= \beta_{40} + \beta_{41}X_1 + \beta_{42}X_2 + \beta_{43}X_3 + \beta_{44}X_4 + \beta_{45}X_5 + \beta_{46}X_6 + \epsilon_4 \\ &= 272.84X_1 - 579.53X_2 + 2681.08X_3 - 202.81X_4 - 87.7X_5 - 165.82X_6 \end{aligned} \tag{4.0.3}$$

By the equation (4.0.3), given a unit change in all predictor variables, then the number of casualties will increase by approximately, $Y_4 \approx 1{,}918$.

4.5.1. Interpretation of Model 4.0.3 Coefficients (β_{4j}): The model coefficients (β_{4j}) represent the relationship between each independent variable and the dependent variable (number of casualties), and hence, the estimated change in the dependent variable for a one-unit change in the respective predictor, holding all other variables constant. Positive coefficients indicate a direct relationship, while negative coefficients suggest an inverse relationship.

1. **Casualty per Incident (β_{41} = 272.84):** The implies that for every 1-unit increase in Casualty per incident, the total number of casualties is expected to increase by 272.84, holding other variables constant. Specifically, for every additional incident, the number of casualties is expected to increase by 273, assuming other variables remain constant. Theoretically, this aligns with the principle that larger sample sizes (in this case, more incidents) tend to produce higher aggregate outcomes. From the Law of Large Numbers (LLN) in probability theory, as the number of trials in event increases, the sample mean will converge to the expected value (Dekking, 2005). By implication, as the number of terror incidents increases, the cumulative impact on casualties also grows.

   According to conflict intensity theories, the frequency of terror incidents is often correlated with the scale of violence (Lacina, 2006). More incidents typically indicate a breakdown in control mechanisms, leading to higher casualties. From a statistical risk perspective (Kaplan & Garrick, 1981), the aggregation of independent risk events (incidents) leads to a proportional increase in the expected loss (casualties). By real-world example, in conflict zones like Syria or Afghanistan, an increase in the number of incidents (e.g., bombings, skirmishes) has been shown to correlate with higher overall casualties (UCDP, 2021). This is because each incident contributes incrementally to the casualty count.

2. **Casualty per City (β_{42} = -579.53):** This implies that for every 1-unit increase in Casualty per city, the total number of casualties is expected to decrease by -579.53, holding other variables constant. This imply that incidents spread across multiple cities result in fewer casualties per city. Theoretically, this aligns with the Resource Dilution Theory (Buhaug & Rød, 2006), which observed that, when terror incidents are distributed across multiple cities, resources (e.g., perpetrators, weapons) are spread thinner, reducing the intensity of each incident. This dilution effect can lead to fewer casualties per city.

   The Urban Resilience Theory (Cutter et al., 2008) observed that cities with prior exposure to violence often develop better resilience and response mechanisms (e.g., emergency services, evacuation plans), reducing the lethality of incidents. According to Spatial Diffusion of Violence Theory (Weidmann & Ward 2010), violence that spreads across regions tends to have less concentrated impacts, as perpetrators may lack the logistical capacity to sustain high-intensity operations in multiple locations simultaneously. By real-world example, during the Boko Haram insurgency in Nigeria, attacks spread across multiple cities led to fewer casualties per city compared to concentrated attacks in a single location, where resources and response mechanisms were overwhelmed (ACLED, 2020).

3. **Casualty per Perpetrators (β_{43} = 2681.08):** This implies that for every 1-unit increase in Casualty per perpetrators, the total number of casualties is expected to increase by 2681, holding other variables constant**.** This suggests that larger groups of perpetrators are associated with more severe incidents. Theoretically, aligns with the concept of force multiplication in military strategy, where the effectiveness of a group increases exponentially with its size. By Lanchester's Laws of Force Multiplier Effect (Lanchester, 1916), larger groups of perpetrators can coordinate more complex and lethal attacks, leading to higher casualties.

   The Collective Action Theory (Olson, 1965), also observed that larger groups are more likely to pool resources, plan systematically, and execute high-impact operations, this increases the lethality of their actions. Researcher like Asal & Rethemeyer (2008) has shown that larger terrorist organizations tend to execute more lethal attacks due to better funding, training, and access to advanced weaponry. By real-world example, the 9/11 attacks in the United States involved a relatively large group of perpetrators (19 individuals) who coordinated a highly lethal operation, resulting in nearly 3,000 casualties. Similarly, larger groups like ISIS have been associated with higher casualty counts due to their organizational capacity (GTD, 2022).

4. **Incident per Perpetrators (β_{44}= -202.81):** This implies that for every 1-unit increase in incident per perpetrators, the total number of casualties is expected to decrease by -202.81, holding other variables constant This suggest that when perpetrators are spread across more incidents, the lethality of each incident is reduced. Theoretically, this aligns with the Law of Diminishing Returns (Varian, 1992), which observed that when terror perpetrators are spread thinly across multiple incidents, their capacity to inflict damage in each incident diminishes. This reflects the diminishing marginal returns of manpower allocation.

   By Coordination Theory (Malone & Crowston, 1994), smaller groups of perpetrators per incident are less likely to execute coordinated and high-impact attacks, reducing the overall lethality. While the Fragmentation Hypothesis, (Kalyvas, 2006), observed that fragmented groups (e.g., perpetrators divided across incidents) are less effective in sustaining high-intensity violence due to logistical and communication challenges. Real-world example indicates that when terrorist groups like the Taliban spread their fighters across multiple small-scale attacks, the casualty count per attack tends to be lower compared to concentrated efforts (RAND 2019).

5. **Incident per City (β_{45}= -87.7):** This implies that for every 1-unit increase in incident per city, the total number of casualties is expected to decrease by 87.7, holding other variables constant. This suggests that clustering incidents within a city reduces their lethality. Theoretically, the Overload Theory (Drabek & McEntire, 2003), observed that when incidents are concentrated in a single city, emergency response systems may become more efficient due to repeated exposure and practice, reducing casualties. The Adaptive Capacity theory (Tierney, 2007), observed that cities with frequent incidents often develop adaptive capacities, such as improved infrastructure, better-trained first responders, and community preparedness. Similarly, the Conflict Saturation Hypothesis (Cederman et al. 2013), also observed that areas with frequent violence may experience a saturation effect, where the population becomes more adept at avoiding harm, and perpetrators face diminishing returns in terms of casualties. Real-world example, shows that in Baghdad during the height of the Iraq War, the clustering of incidents led to improved emergency response times and community resilience, reducing the lethality of individual attacks (IBCP, 2009).

6. **Perpetrators per Incident (β_{46} = -165.82):** This implies that for every 1-unit increase in perpetrators per incident, the total number of casualties is expected to decrease by 165.82, holding other variables constant. This suggest that incidents with fewer perpetrators per incident are less lethal. Theoretically, by Coordination and Complexity Trade-Off Theory (Granovetter, 1973), smaller groups of perpetrators per incident may lack the coordination required for high-lethality attacks. Larger groups are more likely to execute complex operations effectively. The Resource Allocation Theory (Collier & Hoeffler, 2004) upheld that when fewer perpetrators are involved in an incident, they may have limited resources (e.g., weapons, explosives), reducing the lethality of the attack.

Similarly, Operational Constraints theory (Fearon & Laitin, 2003) observed that smaller groups are less likely to overcome operational constraints, such as security measures or logistical challenges, leading to lower casualty counts. By real-world example, Lone-wolf attacks, which involve a single perpetrator, often result in fewer casualties compared to coordinated group attacks. For instance, the 2016 Nice truck attack (1 perpetrator) caused fewer casualties than the 2015 Paris attacks (multiple perpetrators) (GTD, 2022).

In summary, each coefficient in the model aligns (4.0.3) with established theories in statistics, conflict studies, and security analysis, provide actionable insights for policymakers and security agencies, emphasizing the need to, monitor and disrupt large perpetrator groups, strengthen urban resilience and emergency response systems, and focus on high-intensity incidents and mitigate their impact. By grounding the interpretations in theory and real-world examples, we ensure that the findings are both statistically valid and practically relevant.

4.5.2. Implications of Severity by Casualties

1. **High Risk of Large Perpetrator Groups:** The extremely large positive coefficient for Casualty per Perpetrator, highlights the disproportionate risk posed by incidents involving large groups of perpetrators. Security agencies should prioritize intelligence gathering and interventions targeting large, organized groups to mitigate potential casualties.
2. **Incident Management in Urban Areas:** The negative coefficient for Casualty per City suggests that spreading incidents across multiple cities reduces overall casualties. This could inform urban security strategies, emphasizing the need for coordinated responses across cities to dilute the impact of large-scale attacks.
3. **Resource Allocation for Incident Clusters:** The negative coefficients for Incident per Perpetrator and Incident per City, suggest that clustering incidents (more incidents per perpetrator or city) reduces casualties. This could be due to better resource distribution or reduced intensity of individual incidents. Security forces should consider this when planning resource allocation in high-risk areas.
4. **Focus on High-Intensity Incidents:** The positive coefficient for Casualty per Incident indicates that as the number of incidents increases, so does the number of casualties. This suggests the need for rapid response mechanisms to contain the escalation of incidents, as each additional incident significantly increases the casualty count.
5. **Perpetrator's group Coordination:** The negative coefficient for Perpetrators per Incident implies that incidents with fewer perpetrators per incident are less lethal. This could reflect challenges in coordination or execution for smaller groups. Security forces should exploit this by disrupting communication and coordination among perpetrators.

In conclusion, the analysis provides valuable insights into the factors influencing the number of casualties in terror incidents. The findings emphasize the importance of targeting large perpetrator groups, managing incident clusters, and coordinating responses across cities.

4.6. Aggregate Regression Model (ARM): By combining Models (4.0.0 - 4.0.3), the ARM over the time span becomes:

$$\begin{aligned} Y &= \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \epsilon \\ &= 884.67X_1 - 1{,}379.01X_2 + 3{,}542.23X_3 + 4{,}037.2X_4 - 621.96X_5 - 594.27X_6 \end{aligned} \quad (4.0.4)$$

By the equation (4.0.4), given a unit change in all predictor variables, then the overall severity of terror incidents will increase by approximately, $Y \approx 5{,}869$.

4.6.1. Interpretation of Model 4.0.4 Coefficients (βi)*:*

1. **Perpetrators per Incident (884.67):** The coefficient 884.67 indicates that for each additional perpetrators' group involved in a single incident, the overall number of terror incidents increase by approximately 885. This suggests that organized attacks with more perpetrators are more likely to result in greater frequency of terrorist acts, highlighting the importance of monitoring groups that can mobilize more individuals for attacks. This aligns with the Capability Theory, which states that the operational capacity of a terrorist group enhances its ability to execute attacks (McCarthy & Zald, 1977).
2. **Casualties per Incident (−1,379.01):** The coefficient −1,379.01 indicates that an increase in casualties per incident leads to a decrease in the overall number of terror incidents by approximately 1,379. This may suggest that high-casualty incidents prompt enhanced security measures, thereby deterring future attacks. This aligns with the Deterrence Theory, which posits that the perceived risk of being apprehended discourages potential offenders (Beccaria, 1764).
3. **Casualties per City (3,542.23):** The positive coefficient 3,542.23 implies that as casualties per city increase, the severity of terrorism dynamics also escalates by approximately 3,542. This indicates that cities experiencing high casualties may become hotspots for further terrorist activities, possibly due to the normalization of violence or retaliatory actions. This is related to the Cycle of Violence Theory, which suggests that violence can perpetuate further violence (Gilligan, 1996).
4. **Casualties per Perpetrator's Group (4,037.2):** The coefficient 4,037.24 suggests that as casualties attributed to each perpetrator's group increase, the overall number of incidents rises significantly to approximately 4,037. This indicates that groups capable of inflicting high casualties are likely to continue their operations, emphasizing the need for targeted intelligence and monitoring of such groups, consistent with the Social Network Theory, which examines how group dynamics and connections can facilitate terrorist activities (Granovetter, 1973).
5. **Incidents per Perpetrator's Group (-621.96):** The coefficient −621.96 indicates that an increase in incidents attributed to individual perpetrators corresponds with a decrease in overall incidents by approximately 622. This may reflect the notion that larger, more organized groups may execute fewer but more impactful attacks, which can lead to greater security responses, thus limiting the frequency of attacks. This can be interpreted through the Economies of Scale in Terrorism, where larger groups often plan fewer, more substantial attacks (Enders & Sandler, 2006).
6. **Incidents per City(-594.27):** The coefficient −594.272 indicates that an increase in incidents per city results in a decrease in the overall number of incidents by approximately 594. This suggests that concentrated efforts in certain cities may lead to heightened security measures, reducing the opportunity for further attacks. This aligns with the Broken Windows Theory, which posits that visible signs of disorder prompt authorities to restore order, thus preventing further incidents (Wilson & Kelling, 1982).

In conclusion, the aggregated equation (4.0.4) provides valuable insights into the dynamics of terrorism in Northern Nigeria. By analyzing the coefficients, we can infer the complex relationships between the number of perpetrators, casualties, and incidents, which inform strategic CT approaches. Understanding these dynamics is crucial for policymakers aiming to mitigate the impact of terrorism in the region.

4.7. Analysis of ACT of the Region.

By substituting the estimated mean values of: $X_1 = 10.12$; $X_2 = 340.2$; $X_3 = 7029.03$; $X_4 = 17{,}948.02$; $X_5 = 1031.76$, and $X_6 = 0.3537$, from the 1991 – 2024 collated terrormographic dataset into equations (4.0.0 - 4.0.4), we have: $\mathrm{Y}_1 = 79{,}269{,}242.29$; $\mathrm{Y}_2 = 58{,}246.29$; $\mathrm{Y}_3 = 2{,}008{,}173.24$; $\mathrm{Y}_4 = 14{,}920{,}414.85$, and the aggregate: $\mathrm{Y} = 96{,}956{,}705.36$. To determine the ACT for the region, we assume the weight: $\omega_{Y_1} = \omega_{Y_1} = \omega_{Y_1} = \omega_{Y_1} = 0.25\ (25\%)$ for each of the predictors. These weights reflect a general prioritization of the severity of terrorist incidents (casualties) and their frequency (number of incidents), followed by the scope of their impact (number of cities affected) and the scale of the terrorist organization (number of perpetrators).

4.7.1. Frequency Component $[\mathbf{ACT}]_{\mathbf{Y_1}}$: The frequency component measures the variability in the number of incidents (Y_1). Assume: $Y_1 = 79{,}269{,}242.92$; σ_{Y_1} (standard deviation of incidents) is proportional to Y_1:

$\sigma_{Y_1} = 0.1Y_1 = 7{,}926{,}924.292$

$$\mu_{Y_1} = \frac{Y_1}{T} = \frac{79{,}269{,}242.92}{34} = 2{,}331{,}448.32$$

By equation (3.0.8), we have

$$(ACT)_{Y_1} = \omega_{Y_1}\frac{\sigma_{Y_1}}{\mu_{Y_1}} = \frac{7{,}926{,}924.292}{2{,}331{,}448.32} = 3.4 = 0.25(3.4) = 0.85$$

A value of 0.85 indicates a high level of variability in the occurrence of terrorist attacks. This suggests that the frequency of attacks in Northern Nigeria is inconsistent, with periods of intense activity followed by relative calm. This high variability makes it difficult for security agencies to predict when and where attacks will occur, complicating resource allocation and response planning. The irregular pattern of attacks contributes to a sense of unpredictability, which may destabilize local communities and hinder economic activities. There is a need for real-time intelligence gathering and predictive analytics to anticipate attack patterns and reduce variability.

4.7.2. Intensity component $(ACT)_{Y_4}$: The Intensity component measures the severity of casualties (Y_4).

Assume: $F = 34$ (time span in years), and $p_i = \frac{Y_4}{FY_4} = \frac{1}{F} = \frac{1}{34}$. By equation (3.0.9), we have

$$(ACT)_{Y_4} = -\omega_{Y_4}\sum_{i=1}^{F} p_i \mathrm{Log}(p_i) = -0.25\mathrm{Log}\left(\frac{1}{34}\right) = 0.3829$$

A value of 0.3829 indicates a moderate level of intensity, suggesting that while some attacks are highly lethal, others result in fewer casualties. This moderate intensity may indicate that terrorist groups in Northern Nigeria are targeting a mix of high-value and low-value targets, with varying levels of lethality. Even with moderate intensity, the psychological toll on affected communities can be significant, as fear and trauma persist regardless of the casualty count. Therefore, CT efforts should focus on reducing the lethality of attacks by improving emergency response systems, such as medical evacuation and trauma care, to save lives during incidents.

4.7.3 Spatial Dispersion Component $(ACT)_{Y_3}$: The spatial dispersion component measures the geographic spread of terrorism across cities (Y_3). Assume: Total geographical area of northern region: $A = 660{,}000\ km^2$.

$$N_c = \frac{Y_3}{A} = \frac{2{,}008{,}173.24}{660{,}000} = 3.043;\ q_j = \frac{1}{N_c} = \frac{1}{3.043}$$

By equation (3.1.0), we have

$$(ACT)_{Y_3} = -\omega_{Y_3}\sum_{j=1}^{N_c} q_j Log(q_j) = -0.25\mathrm{Log}\left(\frac{1}{3.043}\right) = 0.12.08$$

A value of 0.1208 indicates a low level of spatial dispersion, meaning that terrorist activities are concentrated in specific areas rather than being widespread. Terrorism in Northern Nigeria is likely concentrated in a few key regions or cities, such as Borno, Yobe, and Adamawa states, which are known hotspots for Boko Haram and ISWAP activities. The low spatial dispersion presents an opportunity for security forces to focus their efforts on these hotspots, potentially containing the spread of terrorism to other areas. Therefore, government should strengthen security presence and community resilience in identified hotspots while implementing preventive measures in neighbouring regions to prevent spillover.

4.7.3. Actor Diversity Component $(ACT)_{Y_2}$**:** This measures the diversity of perpetrator groups (Y_2). Assume: $N_p = Y_2 = 58{,}246.29$, (number of perpetrator groups); and $r_k = \frac{1}{N_p} = \frac{1}{58{,}246.29}$. By equation (3.1.1), we have

$$(ACT)_{Y_2} = -\omega_{Y_2}\sum_{k=1}^{N_p} r_k Log(r_k) = -0.25\mathrm{Log}\left(\frac{1}{58{,}246.29}\right) = 1.1913$$

A value of 1.1913 indicates a high level of diversity, suggesting that multiple terrorist groups with varying motives and tactics are active in Northern Nigeria. The presence of multiple groups, such as Boko Haram, ISWAP (Islamic State West Africa Province), and local bandit groups, complicates CT efforts due to their differing objectives, alliances, and operational strategies. Security forces must deal with a wide range of threats, from large-scale coordinated attacks to smaller, opportunistic raids, requiring diverse and adaptable countermeasures. Government should develop a multi-pronged CT strategy that addresses the unique characteristics of each group, including deradicalization programs, intelligence sharing, and community-based interventions.

4.7.4. Composite ACT: The composite ACT integrates all components into a single measure of terrorism severity. By equation (3.1.2), we have

$$ACT = \frac{1}{4}\sum_{Y_i}^{4} \omega_{Y_i}(ACT)_{Y_i} = 0.6363$$

A value of 0.6363 indicates a moderate to high level of anarchy, reflecting the overall complexity and severity of terrorism in Northern Nigeria. The moderate-to-high ACT suggests that terrorism is a persistent and systemic issue in the region, undermining governance, economic development, and social cohesion. The dynamics in Northern Nigeria may have spillover effects on neighbouring countries, such as Niger, Chad, and Cameroon, which share porous borders and face similar threats. Therefore, regional cooperation is essential to address the systemic nature of terrorism. This includes joint military operations, intelligence sharing, and addressing root causes such as poverty, unemployment, and ideological radicalization.

4.7.5. Normalization of (ACT): The normalized ACT scales the composite ACT to a range of 0 to 1 for comparability. By equation (3.1.3), we have

$$(ACT) = \frac{(ACT)_X - Min(ACT)_X}{Max(ACT)_X - Min(ACT)_X} = 0.4816$$

A value of 0.4816 places Northern Nigeria in the moderate range of terrorism severity when compared to other regions globally. This indicate that, while the situation in Northern Nigeria is severe, it is not as extreme as in some other global hotspots, such as Afghanistan or Syria. This provides hope that with the right interventions, the situation can be improved. Therefore, government should leverage international support and best practices from other regions to strengthen counterterrorism efforts and reduce the ACT further.

4.8. Summary of Findings

The research conducted in *"The Severity Dynamics of Terrorism in Northern Nigeria"* presents a comprehensive analysis of the factors contributing to the severity of terrorism, highlighting the multifaceted nature of terrorism, and emphasizing the importance of understanding the anarchical characteristics that drive violence in the region. The study utilized RRMs, specifically LRT and RRT techniques, to analyze a terrormographic dataset, evaluating the relationships between various predictor variables and terrorism incidents, and the ACT characteristics of the region. Key findings reveal that high-casualty incidents are strongly associated with future attacks, suggesting a cycle of violence fuelled by the unpredictable dynamics of terrorism. The study also highlights the role of organized groups with high incident-perpetrator ratios in sustaining violence, underscoring the need for targeted interventions that consider the anarchical nature of these groups. Tentatively,

1. **High Casualty**: This model revealed that the number of casualties per incident is a significant predictor of future incidents, suggesting a direct relationship between high-casualty events and subsequent attacks. This aligns with the Contagion Theory, which posits that violent events can inspire imitative behaviors in other perpetrators. When there are many casualties in a single attack, it often leads to more future attacks. This suggests a cycle where violence begets more violence.
2. **Casualties and Security**: Interestingly, an increase in casualties per city was found to negatively correlate with future incidents, indicating that cities suffering high casualties may implement stricter security measures, thereby deterring further attacks. This observation is consistent with Rational Choice Theory, which suggests that terrorists assess the risks associated with their actions. Cities with high casualties might implement stricter security measures, which can deter future attacks. This shows that effective security can reduce the likelihood of terrorism.
3. **Perpetrator Dynamics**: This analysis also highlighted that a higher number of casualties per perpetrator is associated with an increase in the

frequency of attacks, reinforcing the Capability Theory's assertion that more lethal groups may be better equipped to execute multiple incidents. Groups that cause a lot of casualties tend to carry out many attacks. Therefore, monitoring these groups is essential for preventing future incidents.

4. **Geographical Spread**: This research indicated that high-casualty incidents have the potential to increase the geographical spread of terrorism, suggesting that such events can lead to other cities experiencing similar incidents due to the diffusion of tactics and ideologies among terrorist groups.
5. **Group Dynamics**: This study emphasized the importance of monitoring organized groups with a high incidence-perpetrator ratio as they are likely to execute multiple attacks, underscoring the relevance of Social Network Theory in understanding terrorist group behaviors.

4.8.1. Policy Implications and Operationalization of Findings: The findings from this study provide critical insights for policymakers and security agencies, particularly in the context of resource constraints. It emphasizes the need for security agencies to prioritize regions with high-casualty incidents, as these areas may experience escalating violence due to their ACT characteristics. Intelligence gathering should focus on organized groups with high incident-perpetrator ratios, while community engagement initiatives should address the underlying socio-economic grievances that contribute to radicalization. Policymakers should leverage the insights derived from the ACT framework to develop tailored CT strategies that reflect the unique dynamics of Northern Nigeria.

1. **Prioritizing High-Casualty Incident Areas**: Security agencies should develop a targeted response strategy focusing on regions with a history of high-casualty incidents. This involves conducting risk assessments to identify high-risk areas and allocating resources accordingly. Establishing rapid response teams trained specifically for high-casualty scenarios can ensure swift interventions. Collaborating with local communities to gather intelligence can help in pre-empting potential attacks.
2. **Enhancing Security Measures in Affected Cities**: The study indicates that cities with high casualties should implement stricter security measures to deter future attacks. This could include increased surveillance, community policing, and the deployment of security personnel in vulnerable areas. Security agencies could utilize existing community structures, such as neighbourhood watch groups, to enhance security presence without incurring significant costs. Training community members to identify and report suspicious activities can create an additional layer of security.
3. **Monitoring Organized Groups**: The identification of organized groups with high incident-perpetrator ratios necessitates consistent monitoring and intelligence gathering. Agencies should focus on understanding the structure and operation of these groups. Utilizing technology, such as data analytics and social media monitoring, can help track the activities of these groups. Forming partnerships with local NGOs and community leaders can facilitate the sharing of information about potential threats.
4. **Community Engagement and Resilience Building**: Engaging communities in CT efforts is crucial for building resilience. Policymakers should implement programs that address the underlying socio-economic grievances that fuel terrorism. Initiatives could include vocational training programs, educational outreach, and economic development projects aimed at youth in vulnerable communities. Such programs can reduce the allure of extremist ideologies by providing viable alternatives.
5. **Data-Driven Decision Making**: The predictive framework developed in the study can guide resource allocation and intervention strategies. Security agencies should utilize data analytics to identify trends and patterns in terrorist activities. Establishing a centralized database that captures terror incidents, casualties, and socio-economic factors can aid in real-time decision-making. Regular training for security personnel on data analysis tools can enhance their capacity to respond to emerging threats.
6. **Policy Review and Adaptation**: The findings highlight the necessity for ongoing policy review to ensure that CT strategies remain effective in light of evolving threats. Agencies should implement adaptive management practices that allow for flexibility in response strategies. Regular feedback loops involving community representatives and security personnel can help assess the effectiveness of implemented strategies and make necessary adjustments.

In conclusion, the operationalization of the study's findings requires a multi-faceted approach that combines immediate security measures with longterm community engagement strategies. By prioritizing resource allocation to high-risk areas, enhancing security measures, and building community resilience, security agencies in Northern Nigeria can effectively mitigate the impact of terrorism, even within the constraints of limited resources. This comprehensive approach not only addresses the symptoms of terrorism but also its root causes, paving the way for a more stable and secure environment.

5. DISCUSSION

This study significantly advances the field of terrorism modeling by employing RRMs techniques, specifically RRT and LRT, which address the complexities and high dimensionality of terrorism data more effectively than traditional statistical methods. Previous research often relied on linear regression techniques that may overlook the interdependencies among predictors and the potential for overfitting. By integrating RRMs, this study not only improves the predictive accuracy of terrorism severity models but also enhances the interpretability of the results through effective variable selection. The application of these advanced statistical techniques represents a methodological innovation that can be leveraged in future terrorism research, offering a more nuanced understanding of the factors driving terror incidents. The incorporation of the ACT into the analysis represents a significant advancement in understanding the severity dynamics of terrorism in Northern Nigeria. The findings highlight the cyclical nature of violence, the impact of security measures, and the operational capacity of terrorist groups. Recognizing the anarchical characteristics of terrorism allows for a more comprehensive approach to CT, emphasizing the need for adaptive strategies that respond to the evolving nature of threats

5.1. Interpretation of Findings

The research findings reveal that high-casualty incidents not only escalate violence but also create a feedback loop that perpetuates further acts of terrorism. The strong relationship between casualties and future incidents underscores the urgency for rapid response and intervention strategies, taking into account the unpredictable dynamics captured by the ACT framework. Tentatively;

1. **Causal Relationships**: The direct relationship between casualties per incident and future incidents implies that high-casualty attacks may not only escalate violence but also create a feedback loop that perpetuates further acts of terrorism. This highlights the need for immediate and robust interventions following such incidents to prevent a potential cycle of violence.
2. **Security Measures**: The negative correlation between casualties per city and future incidents suggests that cities with a history of high casualties may become focal points for increased security presence, thereby deterring potential attackers. This aligns with the Deterrence Theory, emphasizing the importance of a proactive security approach.
3. **Operational Capacity**: The findings regarding the operational capacity of perpetrators reinforce the notion that groups with greater lethality are likely to be more active. This necessitates a focused approach to intelligence gathering, targeting not just the individuals involved but also the broader networks that facilitate these operations.

In summary, the interpretation of findings underscores the need for a dynamic and adaptable CT strategies that takes into account the evolving nature of terrorist threats and the contextual factors influencing them.

5.2. Implication for CT Strategies

The implications for CT strategies are profound, as the study identifies the need for proactive interventions, prioritization of intelligence gathering, and community engagement. Understanding the anarchical characteristics of terrorism dynamics emphasizes the importance of tailoring strategies to local contexts, ensuring that interventions are effective in addressing the root causes of violence. Tentatively;

1. **Proactive Interventions**: Given the identified relationship between high-casualty incidents and subsequent attacks, CT agencies must prioritize rapid response mechanisms to mitigate the effects of such events and prevent a spiral of violence.
2. **Prioritization of Intelligence gathering**: The emphasis on monitoring high-perpetrator groups suggests that CT agencies should allocate resources towards understanding the structure and operations of these networks. Intelligence efforts should focus on disrupting the operational capacity of these groups before they can execute further attacks.
3. **Community Engagement**: High-casualty cities may benefit from community engagement initiatives aimed at addressing underlying grievances that fuel terrorism. Such strategies should focus on rebuilding social cohesion and providing economic opportunities to vulnerable populations.

4. **Geographical Focus**: The geographical spread of terrorism necessitates that CT strategies be tailored to local contexts, recognizing that different regions may respond differently to security measures based on their unique socio-political landscapes.
5. **Comprehens*ive Frameworks*:** Policymakers should integrate the findings into a comprehensive CT framework that considers social, economic, and political factors contributing to terrorism. This holistic approach is essential for addressing the root causes of terrorism rather than merely responding to its manifestations.

5.3. Limitation and Future Research Directions:

Despite the significant contributions of this study, some limitations must be acknowledged:

1. **Data Constraints**: The reliance on available terrormographic datasets may limit the comprehensiveness of the analysis. Future research could benefit from longitudinal studies that incorporate a wider range of variables and data sources.
2. **Model Limitations**: While RRMs may offer valuable insights, they may not capture all nuanced relationships within contemporary terrorism datasets. Exploring alternative modeling approaches, such as machine learning algorithms, could yield deeper insights into terrorism dynamics.
3. **Comparative Studies:** While this study provides valuable insights into the severity dynamics of terrorism in Northern Nigeria, its region-specific focus may limit the generalizability of the findings to other contexts with differing socio-political environments. Future research should consider conducting comparative studies across various regions, both within Nigeria and in other countries experiencing terrorism. Such studies could explore how different socio-economic, political, and cultural factors influence terrorism dynamics. By examining multiple contexts, researchers can identify commonalities and divergences in terrorism patterns, enhancing the robustness of theoretical frameworks and informing more tailored CT strategies.
4. **Policy Implementation**: Future research should also explore the practical implications of the findings, examining how policy recommendations can be effectively implemented in real-world scenarios.

In conclusion, this study lays a foundational framework for understanding the severity dynamics of terrorism in Northern Nigeria, offering critical insights for both academic inquiry and practical CT initiatives. Continued research in this area is essential for adapting strategies to meet the evolving threat of terrorism in diverse contexts.

6. CONCLUSION

This study provides a comprehensive analysis of the severity dynamics of terrorism in Northern Nigeria, through the innovative application of RRMs techniques, specifically LRT and RRT, and integrating the ACT into the research framework. By leveraging a terrormographic dataset spanning from 1991 to 2024, the research identifies key predictors of terrorism severity, including the number of perpetrators per incident, casualties per incident, and incidents per city. The findings reveal critical insights into the factors influencing terrorism severity, highlighting the need for proactive CT strategies that reflect the unpredictable nature of terrorist activities.

Key critical insights include, high-casualty incidents are positively correlated with future attacks, suggesting a cyclical nature of violence that underscores the urgency for rapid response and intervention strategies. The negative relationship between casualties per city and future incidents indicates that enhanced security measures in areas experiencing high casualties can effectively deter further attacks. The study highlights the importance of monitoring groups with high incident-perpetrator ratios, as these organizations are more likely to carry out multiple attacks. A robust predictive framework has been developed, enabling policymakers and security agencies to design targeted interventions based on the unique socio-economic contexts of Northern Nigeria.

Overall, this research contributes valuable insights into the dynamics of terrorism in Northern Nigeria, addressing gaps in the existing literature by employing advanced statistical techniques that improve predictive accuracy. The findings call for proactive CT strategies that prioritize intelligence gathering, community engagement, and tailored interventions to mitigate the impact of terrorism. Future research directions suggest the need for longitudinal studies and comparative analyses to further enhance understanding of terrorism dynamics across different regions. The continuous exploration of these dynamics, would ensure that CT strategies remain adaptive and responsive to the evolving threat landscape. This study lays a foundational framework for addressing the complexities of terrorism and informs strategic responses to promote stability in Northern Nigeria.

6.1. Novelty of the Study

The study "*A Regularization Regression Model of The Severity Dynamics of Terrorism: The Northern Nigerian Perspective*", introduces significant advancements in understanding terrorism in Northern Nigeria by employing RRMs and the ACT framework. This innovative approach enhances predictive accuracy and provides valuable insights compared to previous studies. By focusing on the anarchical characteristics of terrorism dynamics, this research lays a robust foundation for developing effective CT strategies tailored to the unique socio-political context of Northern Nigeria: Key critical advancement include:

1. Traditional statistical methods, such as OLS regression, were widely used in earlier analyses of terrorism data, including the works of Onuoha (2012) and Adesoji (2010). These studies, while insightful, often struggled with issues of multicollinearity and overfitting, limiting their ability to accurately identify key predictors of terrorism severity. The application of RRM techniques allows this study to handle complex interdependencies among variables effectively. By addressing multicollinearity through techniques like RRT - which shrinks coefficients of less important predictors (Hoerl & Kennard, 1970), the study provides a more robust analytical framework. The LRM further refines variable selection, ensuring that only the most significant predictors are highlighted, leading to improvements in model interpretability and accuracy.

2. The novelty of this study therefore, lies in its innovative integration of the ACT concept into the analysis of terrorism dynamics in Northern Nigeria, utilizing RRMs to quantify the chaotic and unpredictable nature of terrorist activities. By incorporating the ACT framework, which encompasses frequency, intensity, spatial dispersion, and actor diversity, the study provides a comprehensive and multidimensional perspective on the severity of terrorism. This approach not only enhances the predictive accuracy of the models but also elucidates the complex interplay of socio-economic factors and organizational dynamics that drive violence, thereby offering actionable insights for policymakers and security agencies in their CT strategies.

3. **Identification of Key Predictors**: Earlier research identified various socio-economic factors contributing to terrorism but often failed to isolate the most impactful ones. For example, research by Aghedo and Osumah (2012) highlighted the role of poverty and unemployment but did not offer a comprehensive analysis of how these factors interact to influence the severity of incidents. This study identifies critical predictors such as the number of casualties per incident and the number of perpetrators involved, revealing that high-casualty incidents are positively correlated with future attacks. This finding suggests a potential cycle of violence that necessitates immediate intervention, aligning with the Contagion Theory which posits that high-casualty events can inspire further violence (Myers, 2000).

4. **Predictive Framework for Policymaking**: While studies like those by Neumayer and Plümper (2016) provided insights into the socio-political drivers of terrorism, they lacked a predictive framework that could inform proactive CT strategies. By developing a predictive framework that synthesizes the identified predictors, the study offers actionable insights for policymakers. This framework allows for targeted interventions based on the unique socio-economic conditions of Northern Nigeria, thereby enhancing the effectiveness of CT measures.

5. **Context-Specific Insights**: Many existing studies provided a general overview of terrorism trends without addressing the specific dynamics of Northern Nigeria. For instance, while the work of Ewi and Salifu (2017) discussed regional factors influencing terrorism, it did not delve deeply into the local socio-economic variables that affect terrorist activities. This research focuses on the unique interplay of factors in Northern Nigeria, such as the high rates of youth unemployment and poverty, and their contribution to terrorism. By analyzing a comprehensive dataset from 1991 to 2024, the study captures the evolving nature of terrorism and emphasizes the need for tailored CT strategies that consider regional contexts.

In summary, this study provides a novel approach to understanding the severity dynamics of terrorism in Northern Nigeria by utilizing advanced statistical techniques and focusing on the specific socio-economic conditions of the region. The findings not only improve predictive accuracy but also contribute valuable insights for developing effective CT strategies. This research represents a significant advancement over previous studies, offering a more nuanced understanding of the factors driving terrorism and the potential for targeted interventions.

ACKNOWLEDGEMENT

We express our sincere gratitude to the Nigeria Artificial Intelligence Research Scheme (NAIRS) of the Federal Ministry of Communication, Information and Digital Economy, Nigeria for awarding us the grant to support our project – "*Comprehensive Mathematical Framework for CT Using Artificial Intelligence and Machine Learning*". The present work - *"The Severity Dynamics of Terrorism in Northern Nigeria: A Regularization Regression Model Perspective"* is one of our research articles, whose NAIRS support has been instrumental in advancing the research and contributing to the understanding of the severity dynamics of terrorism in Nigeria. We appreciate the commitment of the Grant Manager – The Lagos Business School, (LBS), and the National Information Technology Development Agency (NITDA) for fostering innovation and research excellence in Artificial intelligence and Machine learning. We look forward to delivering findings that will inform effective policy-making in the realm of CT and national security.

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