# Modeling the Dynamics of Phone - Bike Snatching with Mitigation Strategies in Gombe State, Nigeria

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# Abstract

This study investigates the dynamics of snatching incidents, particularly involving bikes and phones, in Gombe State, where such crimes pose significant threats to public safety and security. Utilizing a comprehensive stochastic modeling approach, the research aims to analyze the intricate interactions between criminals and their environment, considering various socio-economic factors that contribute to the prevalence of snatching. The model developed highlights the probabilistic characteristics of these criminal activities and identifies potential security strategies to mitigate their occurrence. The findings underscore the impact of unemployment, poverty, and income inequality on crime rates, emphasizing the need for targeted interventions to enhance community safety. This research contributes to the understanding of crime dynamics in Gombe State and offers a framework for policymakers to develop effective crime prevention strategies.

Keywords: Snatching, Dynamics, Modeling, Strategies

# INTRODUCTION

Gombe State faces a significant challenge concerning the prevalence of snatching incidents, particularly involving bikes and phones, which poses a threat to public safety and security. Despite efforts by law enforcement agencies and local authorities to address this issue, snatching crimes continue to occur with alarming frequency, impacting residents, businesses, and visitors alike. The problem of snatching in Gombe is multifaceted and complex, rooted in various socio-economic, cultural, and environmental factors unique to the region. High levels of unemployment, poverty, and income inequality contribute to a sense of desperation among some segments of the population, driving individuals to engage in opportunistic and criminal behavior such as snatching. The impact of snatching extends beyond the immediate loss of property, as victims often suffer physical harm, psychological trauma, loss of lives and financial setbacks as a result of these

\*Author for Correspondence A. U. Kinafa, H. S. Danjuma, A.A. Ibrahim., DUJOPAS 11 (1b): 93-102, 2025 incidents. Moreover, the pervasive fear of falling victim to snatching acts as a deterrent to economic activities, tourism, and community engagement, undermining the overall well-being and development of Gombe State.

Therefore, owing to the inherent probabilistic characteristics inherent in the activities related to the theft of phones and bikes, the primary aim of this project is to develop a comprehensive stochastic model with the objective of examining and analysing the intricate dynamics associated with phone and bike snatchers, while also taking into account various security strategies that can be implemented to mitigate such criminal activities within the region of Gombe.

Chikore et al. (2024) employed a mathematical modeling approach to investigate the dynamics of criminal interactions within cyber-networks, highlighting the complex interplay between network structures and criminal activities. Similarly, González-Parra et al. (2018) utilized mathematical models to conceptualize crime as a social epidemic, providing insights into the spread and containment of criminal behaviors within societal contexts. Together, these studies underscore the potential of mathematical modeling in understanding and addressing the multifaceted nature of crime. Mataru et al. (2023) developed a mathematical model to analyze crimes in developing countries, incorporating control strategies to mitigate criminal activities. Similarly, Mohammad and Roslan (2017) employed a dynamical approach to examine crime models, emphasizing the role of system dynamics in understanding crime patterns. Expanding on this, Nwajeri et al. (2023) proposed a co-dynamic model integrating drug trafficking and money laundering, using fractional derivatives to explore their interconnected effects. These studies collectively demonstrate the utility of mathematical modeling in addressing diverse aspects of crime and formulating effective intervention strategies. White et. al, (2024) explored the impact of how criminals interact with cyber-networks using a mathematical modelling approach. The study uses deterministic modelling to describe the spread of cybercrime across a cyber-network by describing the heterogeneity of interactions between individuals using a nonlinear interaction between individuals in the network, and allow criminals to operate either internally or externally to the cyber-network. Hamit et.al, (2023) present a Stochastic Measurement Tool for Determining Crime and Safety Indexes: Evidence from Turkey. The study uses a new measurement tool proposed in order to eliminate the effects such as emotional preference, decision-making difficulty. Malonza (2023), obtained a Mathematical model for crimes in developing countries with some control strategies. The study adopts the epidemiological model concepts on model formulation and model analysis while considering unemployment as main driver of crime. The basic properties of the model are analysed, and wellposed of the model is established by using the Lipschitz condition. The next-generation matrix is used to obtain the criminal reproduction number which help to derive the conditions for local and global stability of the model. Ogunrinde (2023) obtained a Co-dynamic Model of Drug Trafficking and Money Laundering Coupled with Fractional Derivative. The study shows that the proposed compartment system solution exists and is unique using fixed point theorems. The stability frame work of the system which is as a result of slight disturbance in the initial condition was investigated and was shown to be stable if necessary conditions are satisfied. Yuan Zhang & Chuntian Wang, (2021) presents a multistate stochastic criminal behaviour model under a hybrid scheme. The study introduces a new-generation criminal behaviour model with separated spatial-temporal scales for the agent actions and the environment parameter reactions. White et. al, (2021) presents the crime dynamics in a heterogeneous environment: A mathematical approach. The study develops a mechanistic, mathematical model which combines the number of crimes and number of criminals to create a dynamical system. Analysis of the model highlights a threshold for criminal efficiency,

below which criminal numbers will settle to an equilibrium level that can be exploited to reduce crime through prevention.

## MATERIALS AND METHODS

The model comprises of four (4) Susceptible  $S_w$  educated and employed individuals,  $S_x$  educated and unemployed individuals,  $S_y$  uneducated and employed individuals,  $S_z$  uneducated and unemployed individuals Moderate M, unarmed phone/bike snatchers C, armed phone/bike snatchers A, jail J facility and Prison R. Susceptible individuals are recruited into the population by input rate  $\pi$ . When susceptible individuals (i.e.  $S_x$  and  $S_y$ ) have contact(s) with some phone/bike snatchers the probability of embracing the ideology  $\frac{\beta S_x C}{N}$  and  $\frac{\beta S_y C}{N}$  but embracing the ideology

did not make them extremist except with a proportion of  $\alpha MC$  chance for which the individual move to unarmed phone/bike snatchers. The individual in unarmed group then becomes armed phone/bike snatchers group with rate  $\theta$ . Due to security strategies on phone/bike snatchers some individual's jailed and later fall back for some reasons from jail to unarmed phone/bike snatchers or armed phone/bike snatchers depending on from which compartments they are from. The diagram below is a Schematic representation of the Phone/Bike Snatching model.

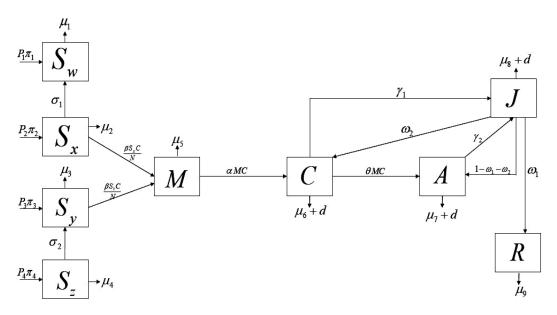


Figure 1: Model diagram

#### Model equation

$$P_{x_{1}x_{2}x_{3}x_{4}x_{5}x_{6}x_{7}x_{8}x_{9}}(t+\Delta t) = P_{1}\pi_{1}\Delta t.P_{x+1}(t) + P_{2}\pi_{2}\Delta t.P_{x+2}(t) + P_{3}\pi_{3}\Delta t.P_{x+3}(t) + P_{4}\pi_{4}\Delta t.P_{x+4}(t) + r_{21}(x_{2}-1)(x_{1}+1)\Delta t \cdot P_{(x_{2}-1)(x_{1}+1)}(t) + \mu_{2}(x_{2}-1)\Delta t \cdot P_{(x_{2}-1)(x_{1}+1)}(t) + r_{34}(x_{3}-1)(x_{4}+1)\Delta t \cdot P_{(x_{3}-1)(x_{4}+1)}(t) + \mu_{3}(x_{3}-1)\Delta t \cdot P_{(x_{3}-1)(x_{4}+1)}(t) + r_{34}(x_{3}-1)\Delta t +$$

$$r_{25} (x_{2} - 1) (x_{5} + 1) \Delta t \cdot P_{(x_{2} - 1)(x_{5} + 1)} (t) + \mu_{2} (x_{2} - 1) \Delta t \cdot P_{(x_{2} - 1)(x_{5} + 1)} (t) + \\ r_{35} (x_{3} - 1) (x_{5} + 1) \Delta t \cdot P_{(x_{3} - 1)(x_{5} + 1)} (t) + \mu_{3} (x_{3} - 1) \Delta t \cdot P_{(x_{3} - 1)(x_{5} + 1)} (t) + \\ r_{56} (x_{5} - 1) (x_{6} + 1) \Delta t \cdot P_{(x_{5} - 1)(x_{6} + 1)} (t) + \mu_{5} (x_{5} - 1) \Delta t \cdot P_{(x_{5} - 1)(x_{6} + 1)} (t) + \\ r_{67} (x_{6} - 1) (x_{7} + 1) \Delta t \cdot P_{(x_{6} - 1)(x_{7} + 1)} (t) + \mu_{6} (x_{6} - 1) \Delta t \cdot P_{(x_{6} - 1)(x_{7} + 1)} (t) + \\ r_{78} (x_{7} - 1) (x_{8} + 1) \Delta t \cdot P_{(x_{7} - 1)(x_{8} + 1)} (t) + \mu_{7} (x_{7} - 1) \Delta t \cdot P_{(x_{7} - 1)(x_{8} + 1)} (t) + \\ r_{89} (x_{8} - 1) (x_{9} + 1) \Delta t \cdot P_{(x_{8} - 1)(x_{9} + 1)} (t) + \mu_{8} (x_{8} - 1) \Delta t \cdot P_{(x_{8} - 1)(x_{9} + 1)} (t) + \\ r_{68} (x_{6} - 1) (x_{8} + 1) \Delta t \cdot P_{(x_{6} - 1)(x_{8} + 1)} (t) + \mu_{6} (x_{6} - 1) \Delta t \cdot P_{(x_{6} - 1)(x_{8} + 1)} (t) + \\ r_{87} (x_{8} - 1) (x_{7} + 1) \Delta t \cdot P_{(x_{8} - 1)(x_{7} + 1)} (t) + \mu_{8} (x_{7} - 1) \Delta t \cdot P_{(x_{8} - 1)(x_{7} + 1)} (t) + \\ r_{86} (x_{8} - 1) (x_{6} + 1) \Delta t \cdot P_{(x_{8} - 1)(x_{6} + 1)} (t) + \mu_{8} (x_{6} - 1) \Delta t \cdot P_{(x_{8} - 1)(x_{7} + 1)} (t) + \\ - \left\{ \begin{array}{l} 1 + P_{1}\pi_{1} + (\mu_{1})(x_{1} + ) + P_{2}\pi_{2} + (\mu_{2} + r_{2})(x_{2} + 1) + P_{3}\pi_{3} + \\ (\mu_{3} + r_{35})(x_{3} + 1) + P_{4}\pi_{4}(\mu_{4})(x_{4} + 1) + (\mu_{5} + r_{56})(x_{5} + 1) \\ + (\mu_{6} + r_{67}) + (\mu_{7} + r_{78}) + (\mu_{8} + r_{89}) + (\mu_{9})(x_{9} + 1) \\ \dots (3.1) \end{array} \right\}$$

Equation (1) satisfies the forward Kolmogorov equation, Allen (2010), described the multivariate process of events taking place or happening in the  $(t, t + \Delta t)$  interval together with their corresponding transition, where

$$r_{21} = \sigma_1, \quad r_{34} = \sigma_2, \quad r_{25} = \frac{\beta S_x C}{N}, \quad r_{35} = \frac{\beta S_y C}{N}, \quad r_{56} = \alpha M C, \quad r_{67} = \theta C, \quad r_{78} = \gamma_2$$
  
$$r_{87} = 1 - \omega_1 - \omega_2, \quad r_{86} = \omega_2, \quad r_{68} = \gamma_1, \quad r_{89} = \omega_1$$

Differentiating equation (1) using first principle, this gives us our Kolmogorov Forward Differential Equation below:

$$\frac{dP_{_{1}x_{2}x_{3}x_{4}x_{5}x_{6}x_{7}x_{8}x_{9}}}{dx}(t+\Delta t) = P_{1}\pi_{1}\Delta t.P_{x+1}(t) + P_{2}\pi_{2}\Delta t.P_{x+2}(t) + P_{3}\pi_{3}\Delta t.P_{x+3}(t) + P_{4}\pi_{4}\Delta t.P_{x+4}(t) + r_{21}(x_{2}-1)(x_{1}+1)\Delta t \cdot P_{(x_{2}-1)(x_{1}+1)}(t) + \mu_{2}(x_{2}-1)\cdot P_{(x_{2}-1)(x_{1}+1)}(t) + r_{34}(x_{3}-1)(x_{4}+1)\Delta t \cdot P_{(x_{3}-1)(x_{4}+1)}(t) + \mu_{3}(x_{3}-1)\cdot P_{(x_{3}-1)(x_{4}+1)}(t) + r_{25}(x_{2}-1)(x_{5}+1)\Delta t \cdot P_{(x_{2}-1)(x_{5}+1)}(t) + \mu_{2}(x_{2}-1)\cdot P_{(x_{2}-1)(x_{5}+1)}(t) + r_{25}(x_{2}-1)(x_{5}+1)\Delta t \cdot P_{(x_{2}-1)(x_{5}+1)}(t) + \mu_{2}(x_{2}-1)\cdot P_{(x_{2}-1)(x_{5}+1)}(t) + r_{25}(x_{2}-1)(x_{5}+1)\Delta t \cdot P_{(x_{2}-1)(x_{5}+1)}(t) + \mu_{2}(x_{2}-1)\cdot P_{(x_{2}-1)(x_{5}+1)}(t) + r_{25}(x_{2}-1)(x_{5}+1)\Delta t \cdot P_{(x_{2}-1)(x_{5}+1)}(t) + r_{25}(x_{2}-1)\cdot P_{(x_{2}-1)(x_{5}+1)}(t) + r_{25}(x_{2}-1)(x_{5}+1)\Delta t \cdot P_{(x_{2}-1)(x_{5}+1)}(t) + r_{25}(x_{2}-1)\cdot P_{(x_{2}-1}$$

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(1)

$$r_{35} (x_{3}-1)(x_{5}+1)\Delta t \cdot P_{(x_{3}-1)(x_{5}+1)}(t) + \mu_{3} (x_{3}-1) \cdot P_{(x_{3}-1)(x_{5}+1)}(t) + r_{56} (x_{5}-1)(x_{6}+1)\Delta t \cdot P_{(x_{5}-1)(x_{6}+1)}(t) + \mu_{5} (x_{5}-1) \cdot P_{(x_{5}-1)(x_{6}+1)}(t) + r_{67} (x_{6}-1)(x_{7}+1)\Delta t \cdot P_{(x_{6}-1)(x_{7}+1)}(t) + \mu_{6} (x_{6}-1) \cdot P_{(x_{6}-1)(x_{7}+1)}(t) + r_{78} (x_{7}-1)(x_{8}+1)\Delta t \cdot P_{(x_{7}-1)(x_{8}+1)}(t) + \mu_{7} (x_{7}-1) \cdot P_{(x_{7}-1)(x_{8}+1)}(t) + r_{89} (x_{8}-1)(x_{9}+1)\Delta t \cdot P_{(x_{8}-1)(x_{9}+1)}(t) + \mu_{8} (x_{8}-1) \cdot P_{(x_{8}-1)(x_{9}+1)}(t) + r_{68} (x_{6}-1)(x_{8}+1)\Delta t \cdot P_{(x_{6}-1)(x_{8}+1)}(t) + \mu_{6} (x_{6}-1) \cdot P_{(x_{6}-1)(x_{8}+1)}(t) + r_{87} (x_{8}-1)(x_{7}+1)\Delta t \cdot P_{(x_{8}-1)(x_{7}+1)}(t) + \mu_{8} (x_{7}-1) \cdot P_{(x_{8}-1)(x_{7}+1)}(t) + r_{86} (x_{8}-1)(x_{6}+1)\Delta t \cdot P_{(x_{8}-1)(x_{6}+1)}(t) + \mu_{8} (x_{6}-1) \cdot P_{(x_{8}-1)(x_{6}+1)}(t) + - \begin{cases} 1+P_{1}\pi_{1}+(\mu_{1})(x_{1}+)+P_{2}\pi_{2}+(\mu_{2}+r_{25})(x_{2}+1)+P_{3}\pi_{3}+ \\ (\mu_{3}+r_{35})(x_{3}+1)+P_{4}\pi_{4}(\mu_{4})(x_{4}+1)+(\mu_{5}+r_{56})(x_{5}+1) \\ +(\mu_{6}+r_{67})+(\mu_{7}+r_{8})+(\mu_{8}+r_{89})+(\mu_{9})(x_{9}+1)_{\dots(3,1)} \end{cases} . P_{x_{1}x_{2}x_{3}x_{4}x_{5}x_{6}x_{7}x_{8}x_{9}}(t)$$

(2)

Equation (2) is a full dynamics and it can be simplified or converted with the aid of multivariate probability generating function. The probability generating function of the distribution corresponding to the multivariate process can be derived directly from the preceding forward Kolmogorov differential equation. The form of the probability generating function is

$$F(y_1, y_2, y_3, y_4, y_6, y_7, y_8, y_9; t) = \sum_{x_1}^{\infty} \sum_{x_2}^{\infty} \sum_{x_3}^{\infty} \sum_{x_4}^{\infty} \sum_{x_5}^{\infty} \sum_{x_6}^{\infty} \sum_{x_7}^{\infty} \sum_{x_8}^{\infty} \sum_{x_9}^{\infty} p(x_1, x_2, x_3, x_4, x_6, x_7, x_8, x_9; t) y_1^{x_1} y_2^{x_2} y_3^{x_3} y_4^{x_4} y_5^{x_5} y_6^{x_6} y_7^{x_7} y_8^{x_8} y_9^{x_9} y_9^$$

(3)

Taking the derivative of equation (3) with respect to t and substituting equation (2), we will get the set of partial differential equation.

### **RESULTS AND DISCUSSION**

We analysed the stochastic model of bike/phone snatchers with security strategies using numerical simulation with initial values for state variables and transition parameters in Table 1.

Parameters	DISCRIPTIONS	VALUE	SOURCE
$\pi$	Recruitment rate	10	Misal (2021)
$\beta_{_{X}}$	The rate at which susceptive educated and employed individual enter Moderate population	0.01	Udoh (2019)
$oldsymbol{eta}_{y}$	The rate at which susceptive educated and unemployed individual enter Moderate population	0.2	Udoh (2019)
σ	The rate at which educated or uneducated individual moved to employed class	0.2	Udoh (2019)
θ	The rate at which unarmed phone/bike snatchers moved to armed phone/bike snatchers	0.2	Udoh (2019)
α	The rate at which moderate individuals moved to unarmed phone/bike snatchers	0.3	Misal (2021)
γ	The rate at which unarmed or armed phone/bike snatchers move to jail due to security strategies	0.1	Udwadia (2019)
ω	The rate at which jailed phone snatchers move back to either unarmed phone/bike snatchers or prison facility	0.1	Udwadia (2019)
$1 - \omega_1 - \omega_2$	The rate at which jailed armed phone/bike snatchers move back to their class after jail	0.7	Abiodun (2018)
d	Deaths due to security strategies	0.3	Santoprete (2018)
μ	Natural deaths	0.09	Estimated
$S_w$	Susceptible educated and employed Population	10,000	Estimated
$S_{x}$	Susceptible educated and unemployed Population	15,000	Estimated
$S_{y}$	Susceptible uneducated and employed Population	5,000	Estimated
S <sub>z</sub>	Susceptible uneducated and unemployed Population	3,000	Estimated
М	Moderate Population	100	Estimated
С	Population of Unarmed phone/bike snatchers	75	Estimated
Α	Population of Armed phone/bike snatchers	45	Estimated
J	Population of Jail phone/bike snatchers	17	Estimated
R	Population phone/bike recover from jail	7	Estimated

Table 1: Parameters, Descriptions and their Value

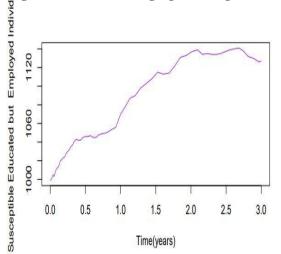
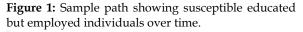


Figure 1-9 below is a graphical representation of sample paths simulation



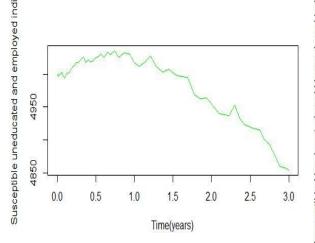


Figure 3: Sample path showing susceptible uneducated but employed individuals over time.

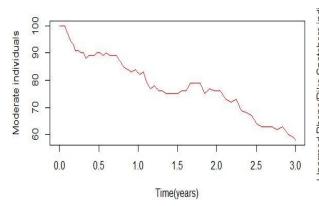


Figure 5: Sample path showing Moderate Individuals over time

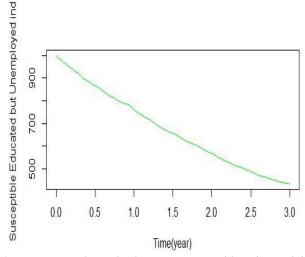
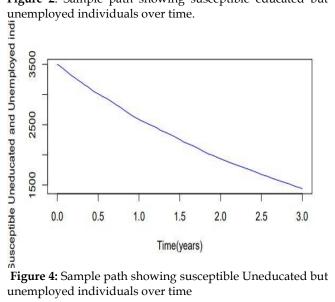


Figure 2: Sample path showing susceptible educated but unemployed individuals over time.



unemployed individuals over time

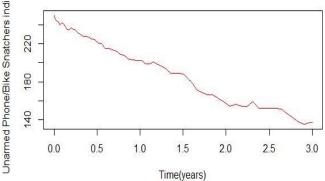
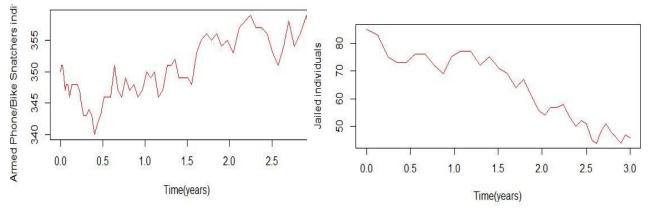
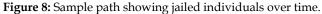
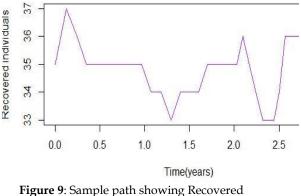


Figure 6: Sample path showing unarmed phone/bike snatchers individuals over time



**Figure 7:** Sample path showing armed phone/bike snatchers individuals over time.





individuals over time.

From Figure 1, the number of susceptible educated individuals but employed is on the rise, a trend attributed to the efforts of government, NGOs, and private organizations in providing job opportunities for them. Figure 2, the decline in the population of susceptible educated yet unemployed individuals can be attributed to the transition of some into employment and the migration of others towards moderate individuals, who are at risk of being influenced by the ideology of snatching. Figure 3, the decrease in the number of vulnerable individuals lacking education yet being employed can be linked to the shift of some towards unemployment and the relocation of others to individuals of moderate means, who may be susceptible to the ideology of theft due to the prevailing economic circumstances of the nation. As a result of the current economic situation, many are unable to sustain their businesses and consequently find themselves without employment. Figure 4, the decline in the population of susceptible uneducated yet unemployed individuals can be attributed to the transition of some into employment and the migration of others towards moderate individuals, who are at risk of being influenced by the ideology of snatching. Figure 5 shows that individuals of moderate inclination who, despite not being actively involved, display an interest in the act of phone/bike snatching, are influenced by their association with certain unarmed perpetrators of such crimes. While their adoption of the ideology does not push them towards extremism, their commitment tends to diminish gradually. These individuals are recognized through the intervention of security forces and the civilian Joint Task Force. Their

transition to becoming active participants is closely observed and regulated. **Figure 6** shows that the decrease in the count of unarmed individuals involved in phone or bike theft persists as a result of security interventions and the relocation of offenders to correctional facilities upon surrender or apprehension by law enforcement leading to their arrest or demise. **Figure 7** shows the escalation in the quantity of armed individuals engaging in phone and bike theft is progressively increasing, a phenomenon attributed to the frequent consumption of illicit substances (hard drugs) by these non-armed offenders. **Figure 8** indicates a decreasing trend in the incarceration of individuals over time, gradually approaching zero. Furthermore, altering the rate does not yield a notable impact on the population of incarcerated individuals. **Figure 9** shows the recovered individuals begins to raises and then fall. This could be the fact that some return back to the activities of phone/bike snatching.

## CONCLUSION

Analysis of snatching incidents in Gombe State reveals a complex interplay of socio-economic factors that drive individuals towards criminal behavior. The stochastic model developed in this study provides valuable insights into the dynamics of bike and phone snatching, highlighting the significance of variables such as unemployment and poverty in influencing crime rates. The findings suggest that effective security strategies are essential in mitigating these criminal activities. By understanding the underlying causes and patterns of snatching, local authorities can implement targeted interventions that not only address the immediate threats to public safety but also contribute to long-term solutions aimed at reducing crime. Future research should continue to explore the evolving nature of crime in Gombe State, incorporating additional variables and potential interventions to enhance community resilience against such threats.

## REFERENCES

- Abiodun, O. I., Jantan , A., Singh, M. M., Anbar, M., & Omolara, O. E. (2018). Terrorism prevention: A Mathematical model for accessing individual with profiling. *International journal of computer science and network security*, 18(7): 117-127.
- Chikore, T., Nyirenda-Kayuni, M., Chukwudum, Q. C., Chazuka, Z., Mwaonanji, J., Ndlovu, M., ... & White, K. J. (2024). Exploring the impact of how criminals interact with cyber-networks a mathematical modeling approach. *Research in Mathematics*, 11(1), 2295059.
- González-Parra, G., Chen-Charpentier, B., & Kojouharov, H. V. (2018). Mathematical modeling of crime as a social epidemic. *Journal of Interdisciplinary Mathematics*, 21(3), 623-643.
- Hamit, E., Kemal, G. K, & Haka, D. (2024). Suggesting A Stochastic Measurement Tool for Determining Crime and Safety Indexes: Evidence from Turkey." *Gazi University Journal of Science* 37, no. 1: 339–355
- Malonza, D. (2023). Mathematical model for crimes in developing countries with some control strategies. *Journal of Applied Mathematics,* .
- Mataru, B., Abonyo, O. J., & Malonza, D. (2023). Mathematical model for crimes in developing countries with some control strategies. *Journal of Applied Mathematics*, 2023.
- Misal, A. A. (2021). Modelling Dynamics of terrorism in Nigeria. Master's Thesis, Unpublished.
- Mohammad, F., & Roslan, U. A. M. (2017, August). Analysis on the crime model using dynamical approach. In *AIP Conference Proceedings* (Vol. 1870, No. 1). AIP Publishing.
- Nwajeri, U. K., Fadugba, S. E., Ohaeri, E. O., Oshinubi, K. I., Ogunrinde, R. R., & Ogunrinde, R. B. (2023). Co-dynamic Model of Drug Trafficking and Money Laundering Coupled with Fractional Derivative. *International Journal of Applied and Computational Mathematics*, 9(5), 73.

- Ogunrinde, R. R. (2023). Co-dynamic Model of Drug Trafficking and Money Laundering Coupled with Fractional Derivative. *International Journal of Applied and Computational Mathematics*, 9(5), 73.
- Santoprete, & Xu, F. (2018). Global stability in a mathematical model of de- radicalisation. *statistical mechanics and its application.*, (509):151 161.
- Udoh, I. J., & Oladeji, M. O. (2019). *Optimal human resourses allocation in counter terrorism operation*. *A Mathematical deterministic model*. Retrieved from International journal of advances in scientific research and engineering5(1): 96-115: https://doi.org/1031695/IJASR E 2019 33008
- Udwadia, F., Leitman, G., & Lambertini, L. (2019). A Dynamic Model Of Terrorism . Discreete Dynamics In Nature And society, 1-32.
- White, K. A. J., Campillo-Funollet, E., Nyabadza, F., Cusseddu, D., Kasumo, C., Imbusi, N. M., Juma, V. O., Meir, A. J., & Marijani, T. (2021). Towards understanding crime dynamics in a heterogeneous environment: A mathematical approach. Journal of Interdisciplinary Mathematics, 24(2), 2139–2159.
- Zhang, Y., & Wang, C. (2021). A multistate stochastic criminal behavior model under a hybrid scheme.