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Optimization of police response times in Kinshasa through machine learning

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Abstract: For some time now, the Democratic Republic of Congo has been facing the problem of juvenile insecurity. This article examined more than 1,042 cases of security incidents in the city of Kinshasa. Most of these incidents are not isolated events but part of broader recurring patterns. This study demonstrates that integrating technological tools with existing law enforcement methods can contribute to the development of a more intelligent, proactive, and efficient information system, thereby strengthening public security in a sustainable manner. The results obtained after data analysis and model testing confirm the hypothesis by demonstrating that the use of predictive tools, in particular logistic regression (GLM) and the generalized additive model (GAM), make it possible to predict the probability of a delayed response time based on the contextual characteristics of the incident.

Keywords: Predictive algorithm, Juvenile delinquency, Predictive policing, Kuluna in Kinshasa, Urban crime; Machine learning, youth violence

1. Introduction

Juvenile delinquency, defined as a set of habitual behaviors observed within a social group, is a form of banditry found among young people. We refer to banditry as a group's collective abuse of power, contrary to the ethics of the society to which it belongs (Dekane, 2016). Like other pathologies that undermine the peace and health of the population, banditry is a problem of concern to the public authorities.

In Kinshasa, the capital of the Democratic Republic of Congo, urban banditry has reached alarming proportions. It is a phenomenon involving not only young men and women but also older people. The first effects began to be felt in the city around 1986-1990. This period was marked by street demonstrations against the ruling power, orchestrated by power-hungry politicians seeking to destabilize the government (Kuna Maba G., 2021). In the period that followed, the city experienced two waves of looting in 1990 and 1991. These scenes of looting plunged most families into a precarious situation, exposed to unemployment, disease, and accidents without any social security coverage. Added to these problems are environmental issues, including erosion, soil degradation, inaccessibility in certain neighborhoods due to poor road conditions, unregulated construction, flooding, conflicts between residents, and water and electricity problems.

The lack of adequate responses to these problems has led to what Castel (2003a) describes as a “risky existence,” which has fostered social insecurity, exposing young people to crime and thus creating civil insecurity. Given that the mission of the police is not to allow crimes to be committed but to prevent them, several strategies have been put in place. These include the establishment of numerous police stations in the neighborhoods most affected by crime. This measure has been supplemented by various approaches, ranging from educational awareness-raising to the use of force.

However, the phenomenon has proven to be much more dynamic than the strategies put in place. This failure can be explained mainly by a lack of anticipation of incidents and limited resources. Faced with rising insecurity and multiple unsuccessful attempts by the authorities to address it, this paper proposes an approach aimed at optimizing the interventions of police units confronted with complex and changing security challenges.

The hypothesis adopted in this study is based on the integration of modern technologies into police systems, through the implementation of smarter, faster, and more effective response systems, which could contribute to the long-term revitalization of police unit interventions. We begin by presenting the context of the study, the issues, the methodology, and the ethical limitations. The second part is devoted to a review of the literature, while the third part, which constitutes the core of the study, is devoted to the analysis of incident patterns and the implementation of appropriate predictive algorithms based on data provided by the victims of the incidents.

2. Methodology

With a view to providing a sustainable scientific response to the issues affecting Congolese society in general, and the city of Kinshasa in particular, a survey was conducted among young people, particularly those belonging to the student community of the Higher School of Commerce of Kinshasa. The survey aimed to produce structured, quantifiable, reliable, comparable, and reproducible data, in accordance with the requirements of scientific research. It was based on a standardized questionnaire, administered in a uniform manner to limit investigator bias and ensure the objectivity of the measurements. The data used was collected from 1,042 respondents and initially stored in Excel files. Initially, the database was structured around 11 distinct variables, each representing specific information.

Table 1. Variables selected during the survey phase

Variable	Type	Format	Specific details
ID_Inc	discrete quantitative	Integer	1,2,3,…
type_incid	qualitative nominal	Factor (3 levels)	Assault / Theft / Vandalism
Date_Inc	Date	Date	"2025-02-04"

heure	Continuous Quantitative	Numeric	18,10,…
Niv_eclair	qualitative binary	Factor (2 levels)	"light","dark"
Commune	qualitative nominal	Chr	"Kingabwa" "Limete",…
Jour_Sem	qualitative nominal	Factor (7 levels)	" Sunday",…
Cond_Mete	qualitative nominal	Factor (3 levels)	"Sunny", "Cloudy"
Trafic_lieu_inc	qualitative binary	Factor (3 levels)	"intense","less_int"
Prox_Police	qualitative nominal	Factor (3 levels)	"Near", "Far"

Given the conditions under which the data was collected, pre-processing at this stage was limited to merging the various files. The R software was then used to clean the data, correct inconsistencies, harmonize variables, manage missing values, and verify data integrity. Approximately 5% of the data was corrected, mainly due to inconsistencies and outliers, and duplicates were removed.
Compliance with ethical principles was central to the research. The anonymity of participants was guaranteed, and questions were formulated in a neutral manner to avoid influencing responses. Participation was voluntary and preceded by clear information about the objectives of the research and the use of the data collected.

Although this methodological approach, based on standardization and qualitative analysis, has several advantages, certain limitations should be noted. Indeed, this approach remains relatively rigid and tends to simplify the reality under study, which does not allow for a full understanding of the social and contextual complexity of the phenomenon being analyzed (Beaud S., Weber F., 1997). The results should therefore be interpreted with caution and could be usefully supplemented by qualitative approaches.

3. Literature review

It is alarming for a nation to see its youth adopting behaviors that could compromise its future. In the scientific field, a rigorous analysis of the origins and mechanisms of these behaviors is necessary in order to identify effective responses. This section examines the existing literature on this issue.

3.1. What can we learn from history?

The criminal movements that are spreading panic in the city of Kinshasa originate from groups with varying degrees of organization: some are rigorously structured, while others lack cohesion and quickly fall apart. The exact reasons for the formation of these gangs are not clearly defined. However, according to some authors, the weakness of the state in terms of supervising and guiding young people is at the root of the phenomenon known as “Kuluna” (Kuna G., 2021 and Tsumbu, L, 2004). This word does not exist in Lingala, the local language spoken in the Congolese capital, but some sources confirm that it originates from Portuguese-Angolan (Bahati M., 2015). In Portuguese, “coluna” means gang, column, or, according to the Petit Robert dictionary, “a group of individuals advancing in single file.” In Angola, fighters from the UNITA rebel movement advanced in columns during the invasion of territories controlled by government forces. Once these territories were conquered, they engaged in systematic acts of violence, marked by widespread destruction and abuse. It is in reference to this extreme violence that young Congolese returning from Angola, where they had been subjected to illegal diamond mining during the armed conflict, used the term “kuluna” to describe the actions of certain gangs of young people in Kinshasa (Bahati M., 2015). Today, the term refers to groups of young people perceived as violent, aged between 12 and 30 on average, organized hierarchically around a leader and operating on the fringes of legality (DIDR, 2021). Their actions, carried out with bladed weapons such as machetes or knives, mainly target vulnerable and unarmed individuals, including the elderly, for the purposes of robbery or violence. These individuals generally belong to gangs whose symbolic names are used to intimidate rival groups (Kipasa, M., 2019).

3.2 Expansion of the phenomenon across the capital

The first event corroborating this phenomenon dates back to 2000. But it was around 2005 that it began to gain momentum. Initially, the phenomenon only affected the outlying neighborhoods. Today, it has spread throughout the capital, even reaching the city center. The violence and brutality observed in their actions affect the entire population, as they not only target ordinary passersby with the aim of stealing their valuables, but also police officers and soldiers, who are among the victims.

3.3 Persistence of the phenomenon despite the actions of the authorities

Since the first effects of this phenomenon appeared during the period 2001-2004, the police have carried out an operation called “Kimia et Keba,” which led to a brief lull. In 2013 and 2014, the Congolese National Police (PNC) and the Republic's intelligence service launched Operation "Likofi" “ Punch ”. The first phase of this operation was a success, as the security forces were able to bring the movement under control. At the request of the population, a second phase of the operation was launched, called “ Punch 2.” During this phase, which aimed to tackle all forms of banditry throughout the city of Kinshasa, the nature of this operation, linked to multiple complaints, grievances, cries, and tears, was the subject of fierce criticism, particularly regarding the violence, summary executions, and forced disappearances targeting many innocent people (Human Rights Watch, 2014). In 2021, a new initiative was launched, characterized by the creation of a special unit within the Congolese National Police called “Anti-Kuluna.” The members of this unit received specialized training in collective intervention techniques in sensitive neighborhoods, aimed at combating urban banditry. However, the lack of logistical resources, the absence of reliable information, insufficient staffing, and a lack of coordination between the various services to respond to demand, and above all, a lack of clear protocols for dealing with certain situations, meant that the cases of kuluna uncovered by this unit remained well below the actual number. It was therefore necessary to involve the population, who were real witnesses to the events, in order to support the military authorities, hence the idea of calling on martial arts practitioners, brought together under the label of “volunteer masters” (Fatu, J., 2022).

These organized volunteer masters were given the task of supporting the national police in the fight against juvenile crime and other criminals who create insecurity in the neighborhoods of the city of Kinshasa. They have become the police's workhorses, deployed in almost every commune of Kinshasa. Characterized by their speed in reaching the scene of a crime, despite their promptness, opinions on their interventions remain mixed. Some residents believe that they help the police by tracking down criminals in order to reduce the crime rate. Others, however, do not support this idea, believing that in some cases Kuluna disguise themselves as volunteer police to settle scores with other gangs or to harass the population themselves (Fatu, 2022).

Apart from initiatives by the military authorities, other socially-oriented initiatives have been attempted. In 2023, the Bracongo brewing company launched a project called “Bilenge Ya Lokumu, Tia na se” (Valuable young people, calm down) in partnership with the provincial government of the city of Kinshasa. According to its initiators, the project aimed to provide a solution to social and governmental needs with the goal of eradicating this phenomenon, which had become very common in the Congolese capital. All these attempts have ended in failure, as these groups continue to pursue their criminal activities on the ground, constantly adapting to law enforcement measures.

3.4 The dawning era of AI

AI can be defined as computer intelligence resulting from technological advances, designed to improve decision-making and learning by drawing inspiration from human cognitive abilities (Lollia, 2026). It is at the heart of global news. This section examines the potential of artificial intelligence in understanding, preventing, and managing these vulnerabilities. It highlights the contributions of intelligent technologies in predictive analysis, decision support, and intervention optimization, while emphasizing the ethical and operational challenges associated with integrating them into existing systems.

3.5 Integration of surveillance technologies

Machine learning and deep learning are two fundamental technologies capable of identifying complex patterns and abnormal behaviors that are difficult to detect using traditional methods (Alonzo & Audevart, 2019). Approaches based on these technologies thus offer a proactive response, capable of adjusting in real time to new threats, reinforcing the effectiveness of crime prevention, surveillance, and control systems within the city.

3.6 The Birth of Predictive Policing

Thanks to these advanced technologies, the concept of predictive policing has emerged. This is a neologism that refers to police services that use computer systems to analyze large amounts of historical data on criminal acts in order to determine where to deploy law enforcement or identify individuals likely to commit crimes or be victims (Lau T., 2020). This forward-looking approach allows for better resource allocation, faster intervention, and more targeted prevention, thereby helping to strengthen urban security while adapting to constant changes in crime patterns.

3.7 The emergence of initiatives in Africa

The literature highlights that security services in cities such as Nairobi, Lagos, and Johannesburg use data from emergency calls, camera networks, and police statistics at various levels to regulate the quality of police interventions and strengthen prevention (Pearson, A. L., & Breetzke, G. D. (2014). The tools used by these services are becoming a management tool for ensuring security in these areas (Benbouzid, 2019).

These initiatives are part of a broader drive to modernize security services in Africa, often supported by partnerships with technology companies and international organizations. Although these projects still face challenges such as data quality, digital infrastructure, and ethical issues, they demonstrate a growing desire to integrate predictive approaches to combat crime more effectively and improve the safety of urban populations (Benbouzid, 2019).

Logistic regression (GLM) is well suited to providing a central solution in these approaches, due to its simplicity, robustness, and interpretability. It is particularly well suited to modeling binary phenomena, such as the probability that an intervention will arrive late or not at all in a given area. For its part, the generalized additive model (GAM) is frequently used to analyze positive continuous variables, such as the duration, intensity, or frequency of incidents. It allows for better capture of the asymmetric distribution of certain criminal phenomena and more refined predictions. The combination of these models contributes to more reliable, transparent predictive analyses that are adapted to the realities on the ground.

3.8 Respect for ethics

The issue of public safety must be addressed in a manner that respects ethics and fundamental rights in order to avoid discriminatory bias and self-fulfilling prophecies. According to European recommendations, the deployment of AI in public safety must balance performance, respect for fundamental rights, and social justice (European Commission, 2021). By ensuring fairness, predictive algorithms strengthen citizens' trust in institutions and ensure the responsible use of predictive policing technologies.

4. In-depth analysis of incident patterns

The data collected from victims takes us to the heart of the events that lead to identifying the modus operandi reflecting criminal intent through the identification of recurring patterns in incident data. This approach aims to identify significant trends, critical areas of vulnerability, and recurring risk factors. This is a fundamental step in shifting police operations from a reactive posture to a proactive and predictive deployment strategy.

4.1 Incident mapping: identification of high-risk areas and recurring incidents

The data shows a high concentration of incidents in a few specific areas. These hot spots represent areas where the probability of an incident is statistically higher. These include the municipality of Limeté, where we can count 104 incidents, 79 in Ngaliema, 77 in Masina, 47 in Kimbaseke, 47 in Lemba, and 41 in Matete. These municipalities represent the epicenter of the phenomenon, accounting for 39% of incidents across the city. The nature of the incidents recorded falls mainly into three categories, with a marked predominance of attacks on people and property. Attacks on people take the form of assaults and attacks on property take the form of theft. Together, they account for 84% of all incidents recorded, highlighting a predominant threat. Although vandalism is minimal, accounting for 16% of incidents, it manifests itself in fights in public places leading to theft and looting. Knowledge of these factors clearly highlights the main hotspots that should be the focus of any strategy to redeploy the most appropriate security efforts.

4.2 Analysis of temporal patterns: Highlighting critical and weekly periods

The study of temporal clusters is essential for anticipating peaks in incidents and adjusting staffing levels accordingly. The aim of the analyses carried out was to understand at what time of day these criminal gangs operate most often. The results show distinct peaks in activity, suggesting that the risks are not evenly distributed throughout the day. There is a particularly high concentration of incidents between 12:00 p.m. and 3:00 p.m., characterized by theft and vandalism. Meanwhile, dawn and morning (5:00 a.m. to 11:00 a.m.) and evening and night (6:00 p.m. to 9:59 p.m.) are mainly characterized by theft and assault. This significant concentration of assaults coincides with the decrease in natural light and population flows, creating an environment conducive to criminal activity. Although the analysis indicates that no day is spared, incidents are mainly concentrated in the evening (6:00 p.m. to 10:00 p.m.) and at night (after 10:00 p.m.). Mondays, Tuesdays, and Fridays are the days most frequently reported.

4.3 Analysis of aggravating factors and vulnerabilities

We will now examine factors that go beyond where and when, in order to understand the conditions that facilitate incidents, using data provided by the columns: lighting level and weather conditions. The study shows us the decisive impact of lighting conditions, highlighting a strong correlation between darkness and the most serious incidents. It should be noted that even nighttime incidents are sometimes reported in “bright” conditions, suggesting that the risk persists in artificially lit areas, which could attract both targets and attackers. The data on weather conditions appear too balanced to consider the weather as a reliable predictor or a major vulnerability in itself.

4.4 Current landscape of the situation

The current landscape of criminal acts committed by these young offenders now leads us to examine the level of intervention by law enforcement agencies to ensure the protection of the population. Knowledge of the responsiveness of police units assigned to the various neighborhoods affected by this phenomenon is of great importance in order to identify the flaws that will guide the search for an optimal solution. The study focuses on response time and the correlation between the proximity of law enforcement and response time.

The data show that despite the police presence, these young people are not prepared to give up their activities, as they continue to operate with impunity. This is all the more true given that the analysis of the data reveals a significant variation in response times, ranging from 1 minute to 16 hours. This wide range confirms the vulnerabilities associated with the lack of coverage. An alarming 622 incidents (61% of the total) occur when law enforcement is perceived as distant or absent, increasing response times and directly compromising citizen safety. It follows from the above that the problem of insecurity in the city of Kinshasa goes beyond the traditional security tools used. It requires a multidimensional approach integrating surveillance technologies with AI-based data analysis capabilities to improve the accuracy and effectiveness of response (De Hert & Papakonstantinou, 2021).

5.5 Model implementation

As response times are characterized by a significant proportion of zeros and an asymmetric distribution of positive durations, we use a two-step model: logistic regression to model the probability of intervention. To do this, the explanatory variables (X) selected are:

Table 2 Summary of key variables

Variable	Type	Format
type_incid	qualitative nominal	Factor (3 levels)
Niv_eclair	qualitative binary	Factor (2 levels)
Cond_ Weather report	qualitative nominal	Factor (3 levels)
Prox_Police	qualitative ordinal	Factor (3 levels)

The generalized linear model (GLM) is based on three fundamental components. First, the response variable Y is assumed to follow a distribution belonging to the exponential family (e.g., normal, binomial, Poisson, or Gamma distributions). Next, the model introduces a linear predictor defined by:

$$\eta = \beta_0 + \sum_{j=1}^{p} \beta_j X_j$$

or, in matrix notation:

$$\eta = X\beta$$

Finally, a link function ***g*** connects the expectation of the response variable, denoted $\mu = E[Y]$, to the linear predictor according to the relationship:

$$g(\mu) = \eta$$

Thus, the general formulation of a generalized linear model is written as:

$$g(E[Y]) = X\beta$$

In our case, the response time (Y), initially measured as an ordinal variable (fast, slow, no response), was transformed into a binary variable Response_Time_bin (0 = not slow, 1 = slow) to enable predictive analysis. These variables are assumed to provide a linear relationship (on the logit scale).

The AUC of 0.68 presented by this model indicates moderate but significant discriminatory power. At the optimal threshold of 0.272, it achieves a sensitivity of 68.4% and a specificity of 62.8%. These performances suggest that the model is more effective at excluding negatives (high estimated negative predictive value) than at confirming positives (moderate accuracy). The choice of threshold reflects a strategy aimed at minimizing false negatives at the cost of an increased false positive rate.

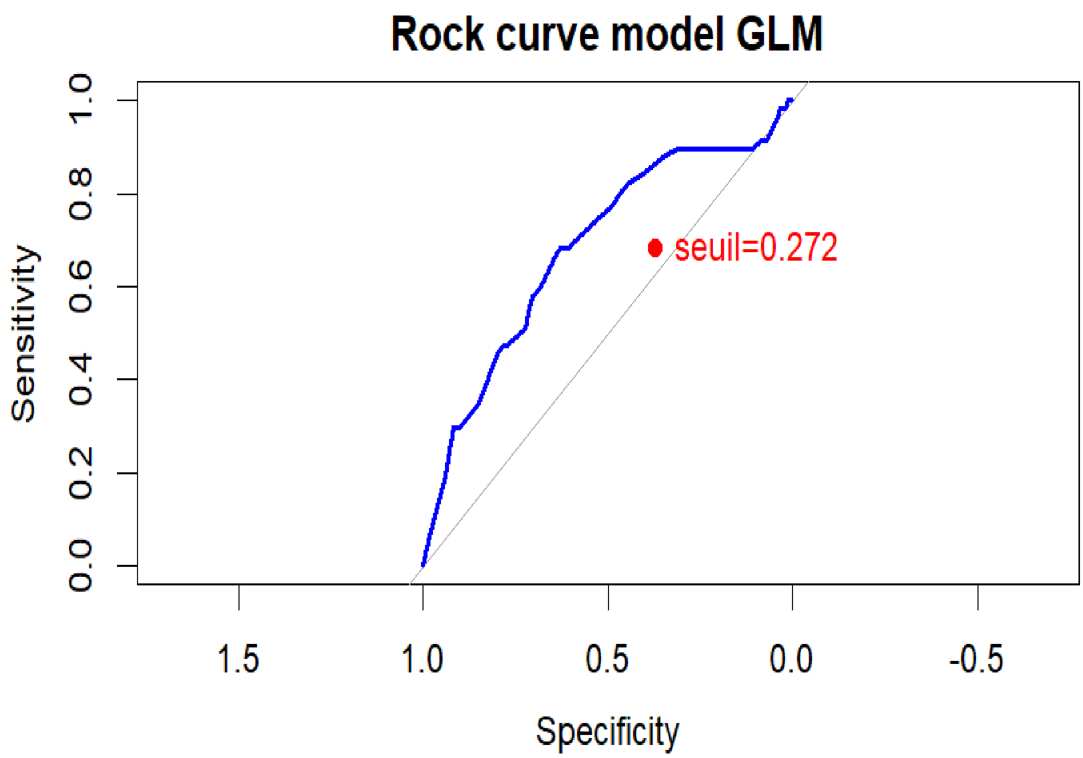

Figure 1 *Roc-GLM curve*

Although performance is modest, the model is useful in contexts where comprehensive detection is a priority. The generalized additive model (GAM) extends the generalized linear model by replacing the linear combination of explanatory variables with a sum of smooth functions. The response variable *Y* is assumed to follow a distribution belonging to the exponential family. The expected value $\mu = E[Y]$ is related to the explanatory variables by a link function g such that:

$$g(\mu) = \eta$$

with the additive predictor defined by:

$$\eta = \beta0 + f1(X1) + f2(X2) + ... + fp(Xp),$$

or, more compactly,

$$g(E[Y]) = \beta0 + j = 1\sum pfj(Xj).$$

Here, β0 represents the y-intercept and fj(...) denotes nonparametric smooth functions estimated from the data (e.g., using splines).

Due to the limitations of the GLM model, the implementation of the GAM model allows for more flexible modeling of effects, without strictly imposing linearity. It was estimated using the same explanatory variables as the GLM. The GAM model has an AUC of 0.6826 and, at an operational threshold of 0.274, a sensitivity of 68.4% and a specificity of 62.8%. The particularly low accuracy (41.9%) indicates that only 42% of individuals classified as positive are truly positive, generating a high rate of false positives. Conversely, the negative predictive value of 83.5% suggests that the model is more reliable for ruling out the condition than for confirming it.

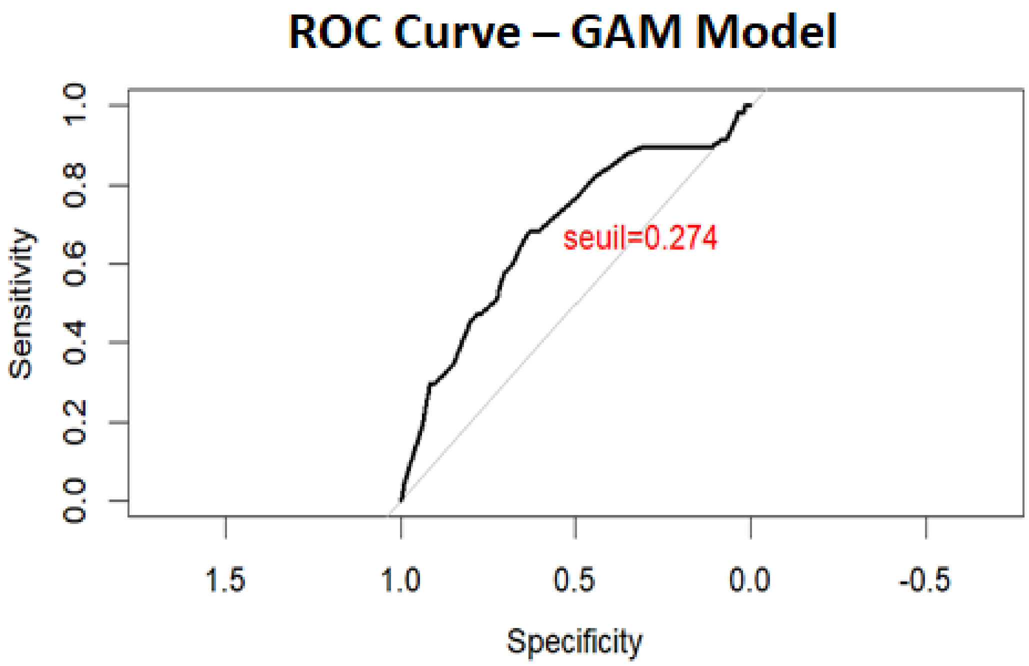

Figure 2. Roc-GAM curve

5. Discussion of results

The GLM and GAM models show almost identical performance metrics (AUC ≈ 0.68, accuracy ≈ 64%, sensitivity ≈ 68%), demonstrating that the proximity of police stations, lighting levels, weather conditions, and the type of incident significantly influence response time. Despite the superior flexibility of GAM in capturing non-linear relationships, this additional complexity does not translate into improved predictive capabilities.

Table 3. Comparison of models

Criteria	**GLM**	**GAM**
AUC	≈ 0.68	≈ 0.68
Accuracy (test)	Comparable	68 %
Flexibility	Weak	Higher
Interpretability	Very good	Good

GLM offers better interpretability thanks to its linear coefficients, a significant advantage for medical/institutional decision-making. In accordance with the principle of parsimony, we recommend using the GLM model, whose simplicity facilitates operational deployment without sacrificing performance. These results can be used to improve prevention and the effectiveness of interventions.

6. Conclusion

This work demonstrates a methodical transformation of raw data on juvenile crime in the Democratic Republic of Congo into strategic intelligence that can be used to aid decision-making. Analysis of the temporal dynamics and types of incidents involving young people has highlighted operational gaps in prevention and intervention mechanisms, particularly in terms of the response time of the relevant services.

Response time, coded in binary form, has an intrinsic variance defined by $p(1-p)$. The logistic GLM and GAM models developed show moderate discriminatory power (AUC = 0.68), indicating that certain explanatory variables, such as the spatio-temporal context of incidents and the availability of response units, contribute to the differentiation between rapid and delayed responses, without however capturing the full heterogeneity observed in situations involving minors.

The model shows a modest but real discriminatory capacity to predict delays in intervention. In light of this result, the phased implementation of the recommendations from these analyses provides an opportunity to improve strategies for preventing and managing juvenile crime, which is particularly acute in the city of Kinshasa. However, major challenges remain in terms of operational feasibility, the real impact on the protection of minors, and the need for enhanced human supervision. Future research should therefore evaluate the effective integration of these decision-making tools into institutional practices, while ensuring respect for children's rights and maintaining human expertise at the center of critical decisions.

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