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Predictive Algorithms and Juvenile Delinquency in Kinshasa: Emerging Challenges and Ethical Implications

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Abstract*—This paper evaluates a sample of 444 reported incidents of urban crime in Kinshasa and identifies important trends that can be used to predict juvenile delinquency using predictive modeling. The proportion of incidents is 44.6% assault (198 cases), 39.2% theft (174 cases), and 16.2% vandalism (72 cases), so 48.9% of the incidents occurred in conditions, whereas 48.9% of the assaults occur during the night or evening hours (Jonas et al., 2022; Hunt et al., 2020). Incidents are clustered in municipalities like Limete (14.6% - 65 cases), Ngaliema (9.5%), and Mont-Ngafula (8.1%), frequently in areas remote from law enforcement (46.8%), and with lengthy police response time (median 20 minutes overall, over 75 minutes in distant areas) (Milaninia, 2020; Duursma & Karlsrud, 2019; Majigo, 2023). These spatiotemporal and environmental determinants point to variables that can be used to predict risks using machine learning in urban African settings (Khosa et al., 2024; Ndikumana et al., 2025). The value of the contribution of this study is that it reveals the viability of applying the application of predictive algorithms to the specifics of delinquency data in Kinshasa to identify the hotspots and allocate resources proactively, and critically evaluates the emerging issues associated with the application of predictive algorithms in resource-limited environments (Mancuso & Corselli, 2023; Tolan et al., 2019; Almasoud & Idowu, 2025). The article offers a conceptual roadmap to ethical artificial intelligence application in juvenile justice in urban African settings by promoting a change in the framework where pure risk prediction would be replaced by equity-oriented interventions, which would promote social justice and youth rehabilitation over stigmatization (Berk, 2019; Keddell, 2019; Barabas et al., 2018; Kurumalla, 2025). This model remains consistent with the prevailing demands for transparent, proportional, and rights-oriented predictive tools to prevent harm and improve preventive outcomes (Modise, 2024; Stevenson & Slobogin, 2018; Oswald et al., 2018).

Keywords*— Predictive algorithms; Juvenile delinquency; Kinshasa; Machine learning; Algorithmic bias; Ethical implications; Predictive policing

I. INTRODUCTION

The city of Kinshasa is one of the most populous cities on the African continent, the capital of the Democratic Republic of Congo (DRC), which is a rapidly urbanizing city, plagued by socioeconomic disparities, and with its youth population experiencing significant vulnerability to delinquency and violence (Jonas et al., 2022). The trends of delinquency rates related to juveniles in Kinshasa show a complicated interplay between the environmental, temporal, and infrastructural factors that put young people at risk (Jonas et al., 2022). Using 444 reported cases of urban crime, most of which were assaults (198 cases, or about 44%), thefts (174 cases, or 39%), and vandalism (72 cases, or 16%), one finds that the factors have combined to create a risky environment in the area These cases indicate hotspots like Limete (65 incidents), Ngaliema (42 incidents), and Mont-Ngafula (36 incidents), where less intensive traffic (286 cases in total) and longer distance to law enforcement (208 cases in total) are associated with slow responses with an average of 42 minutes and a maximum of 960 minutes (16 hours) (Duursma & Karlsrud, 2019). These delays not only help to delay the immediate intervention but also keep the juveniles in endless loops of uncontrollable behavior since it is always possible that they are both victims and offenders in the situations (Hunt et al., 2020). The nocturnal character of much delinquency especially assaults, where 98 of the 198 cases (49%) occur under the dark lighting conditions and 18:0023:59 hours of the day, is also highlighted by the fact that 217 instances of the data occurred under the dark lighting condition (49%) and 18:0023:59 hours of the day (159 instances or 36%), respectively (Jonas et al., 2022). Such time association is consistent with overall trends of urban susceptibility, in which cloudy (148 cases) or rainy (67 cases) weather conditions only exacerbate visibility and the effectiveness of response, and in many cases, in less intensive traffic areas that are not close to police posts (53 cases with no police post nearby) (Majigo, 2023).

In this regard, predictive algorithms can be a promising technological intervention that uses machine learning and big data analytics to predict the probability of delinquency, find young people at risk, and optimally allocate resources in under-resourced settings such as Kinshasa (Khosa et al., 2024; Ndikumana et al., 2025). They have experimentally used these algorithms to predict legal outcomes and mental health trajectories in youth by analyzing historical data to provide probabilistic risk-score analyses, analogous to juvenile delinquency prevention (Khosa et al., 2024; Ndikumana et al., 2025). As an example, using the variables incident type, time of the day, weather conditions, and distance to the law enforcement, and using the data on Kinshasa, one could predict hotspots: on Tuesdays (73 incidents) and Thursdays (68 incidents), the activity is higher, which may be related to the weekly routine due to which the juveniles were exposed to unsupervised settings (Duursma & Karlsrud, 2019). Likewise, the cities such as Ngaba (35 incidents) or Lemba (32 incidents) demonstrate clusters of attacks and robberies in the early morning (79 incidents) or afternoon (106 incidents) when bright light (227 cases) may give the wrong impression of security, but does not prevent crimes in remote locations (Majigo, 2023). Such predictions can further be applied to the prevention of children, which is achieved through integration of artificial intelligence (AI) and mobile health (mHealth) tools that can identify the underlying factors, such as family instability and community abuse, that are common in Kinshasa (Hunt et al., 2020; Jonas et al., 2022). Rwandan research shows that machine learning-based predictive models can detect mental health risks among young people, which often overlap with delinquency, and proposes a flexible model that can be applied to Congolese cities (Ndikumana et al., 2025).

Nevertheless, the introduction of predictive algorithms into the juvenile justice system in Kinshasa is already associated with new challenges that are defined through the data discrepancies and infrastructural constraints that are visible in the data, like the different formats of response time and the differences in the name of the municipality, e.g., Mont-ngafula vs. Mont-Ngafula (Milaninia, 2020). These technical challenges are indicative of broader problems in the application of algorithms in Africa, where profiling in decision-making can misalign with culture and context, potentially biasing final results to the disadvantage of marginalized communities (Mancuso & Corselli, 2023). To give one example, the skewed data (distant proximities (208 cases) and no posts (53 cases)) may be trained to choose to over-predict risks in outerly lying areas such as N'Djili (23 incidents) and Kimbanseke (22 incidents), where a median response time of 20 minutes already signals systemic delays, exacerbating inequalities in resource distribution (Duursma & Karlsrud, 2019). Furthermore, accuracy issues are relevant in the juvenile context, where algorithms are more likely to exaggerate statistical trends without accounting for them and to inflate estimates of youth risk (Berk, 2019; Stevenson & Slobogin, 2018). This is further complicated by the fact that the training data may be biased, as observed in global studies showing that machine learning results in additional inequalities in predicting recidivism (Milaninia, 2020; Tolan et al., 2019; Miron et al., 2021).

The application of predictive algorithms in the context of juvenile delinquency in Kinshasa also has some profound implications, which can be viewed in terms of the imperatives of public safety against the ideals of justice, fairness, and human rights (Modise, 2024; Kurumalla, 2025). At the center of these fears is the clash between statistical fairness and social justice, in which the instruments designed to enhance efficiency could, by default, stigmatize at-risk youth and thereby create patterns of exclusion within already vulnerable populations (Keddell, 2019; Keddell, 2023). Predictive models should not result in predatory uses, as in the case of high physical and sexual abuse rates among female middle schoolers in Kinshasa, which are associated with such factors as household composition and community violence (Jonas et al., 2022), and so are reflective of deep-seated risks (Martin, 2023; Susser, 2021). Privacy breaches involving the collection of information about minors, misuse of genetic or behavioral forecasts in legal cases, and the risk that algorithmic decisions violate due process are all ethical risks (Refolo et al., 2025; Tonry, 1987; Kutnowski, 2017). Moreover, biases in big data analytics may breach international standards in humanitarian and criminal justice systems, particularly in post-conflict contexts such as the DRC (Milaninia, 2020; Yagoub, 2025). Although effective in certain parts of the world, predictive policing models require proportionality to avoid excessive policing, as the experience of the

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HART model in Durham and CAS systems in the Netherlands has shown (Oswald et al., 2018; Mutsaers & van Nuenen, 2023). In juveniles, this two-edged sword is the balance between preventive benefits and the risk of labelling young people based on incomplete information, which may create inequities (Stevenson & Slobogin, 2018; McSherry, 2020).

Replacing ethical discourse with supportive, rather than predictive, practices should be considered a key intervention, with occupational therapy and community-based counseling included to reduce delinquency (Barabas et al., 2018; Hou, 2022). In African criminal justice, algorithmic fairness must be challenged directly, as emphasized in the literature on the effectiveness of predictive policing (Almasoud & Idowu, 2025; Khatun & Kumar, 2025). In the same way, child protection algorithms must align with the principles of social justice to prevent the perpetuation of structural disadvantages (Keddell, 2019; McKay, 2020). Ethical applications in crime prevention may leverage ICT to trigger crime in sunny-day situations (229 cases in all) or in traffic jams (158 cases) on a typical day in Kinshasa, when youth face everyday pressures in the urban environment (Majigo, 2023).
This paper will explore these dimensions through predictive algorithms in criminal justice, then use them to understand delinquency trends in Kinshasa, address emerging challenges, and finally unravel the ethical considerations (Khosa et al., 2024; Modise, 2024). It supports the idea of fair, contextual solutions that use technology to promote justice rather than widen gaps by basing the discussion on available incident statistics and on the existing literature (Kurumalla, 2025; Almasoud & Idowu, 2025).

II. LITERATURE REVIEW

Introduction to Predictive Algorithms and Juvenile Delinquency

The combination of predictive algorithms and juvenile delinquency is the area of criminal justice research that is steadily growing, as sophisticated computational methods are used to predict criminal actions, evaluate risks, and direct preventive measures, especially in the context of the urban setting among young offenders (Khosa et al., 2024; Ndikumana et al., 2025). Risk scores based on predicted trends are generated by predictive algorithms that use machine learning and big data analytics and can inform interventions, such as targeted policing or social support (Hunt et al., 2020; Duursma & Karlsrud, 2019). These instruments are especially promising in the context of juvenile delinquency, as they could help improve pathways to criminality influenced by socioeconomic and family factors, as well as by community violence (Jonas et al., 2022; Hou, 2022). Nevertheless, their usage in the development of such cities as Kinshasa, the capital of the Democratic Republic of Congo (DRC), presents its own set of problems and includes data scarcity, cultural bias, and ethical concerns that have the potential to further worsen the existing inequalities (Mancuso & Corselli, 2023; Modise, 2024). The literature review is a synthesis of the significant scholarship relating to predictive algorithm in criminal justice and juvenile application specifically and further elaborates the emerging challenges and ethical implications attached to this kind of algorithm and draws parallels to the context of Kinshasa where incident reports reveal trends of assaults, thefts, and vandalism that appear to be related mainly to the nighttime vulnerability and distance between the law enforcement and the community (Milaninia, 2020; Majigo, 2023).

Principles of Predictive Algorithms in Criminal Justice

Actuarial risk assessment tools, which have evolved into more advanced AI-driven systems, are the predecessors of predictive algorithms in criminal justice systems and can be applied to large datasets to make probabilistic predictions (Tonry, 1987; Berk, 2019). The initial literature focused on categorizing offenders by demographic and behavioral characteristics, highlighting the usefulness and inherent dilemma of such forecasts (Tonry, 1987). Machine learning algorithms, including those trained on legal outcomes in South Africa, are more or less effective depending on the models used, such as random forests and neural networks, and have reached a point where they can guide judicial decisions (Khosa et al., 2024). In Rwanda, predictive modeling has also been used to predict youth mental health, with predictors of risk (including trauma and social isolation) overlapping with delinquency predictors, using surveys and health records (Ndikumana et al., 2025). These algorithms are usually based on characteristics such as the type of incident, the time of day, and other environmental factors, such as nighttime (44% of 445 incidents)

(48% of cases), to produce insights that might predict juvenile engagement in crimes (Hunt et al., 2020).

The fact that the tools are tailored to juvenile delinquency highlights the move toward preventive justice, as algorithms can not only predict recidivism but also facilitate the implementation of interventions, such as mHealth-based violence prevention tools for children (Hunt et al., 2020; McSherry, 2020). For example, big data analytics can be used to identify hotspots and individual risks, as in the case of UN peacekeeping operations that enhance predictive analysis to prevent conflicts, which are flexible in addressing urban delinquency in African cities (Duursma & Karlsrud, 2019). According to Tanzania, information and communication technologies (ICT) have increased the capabilities of detecting and preventing crime, implying that scalable solutions can be applied in resource-constrained environments such as the city of Kinshasa, where youth are prone to being aggravated by delayed response (average over 40 minutes) within peripheral municipalities (Majigo, 2023; Jonas et al., 2022). The literature reminds us that such tools are more efficient, but because they tend to reflect the biases in training data, they can disproportionately affect marginalized groups (Milaninia, 2020; Tolan et al., 2019).

In Juvenile Applications and Effectiveness

The scholarly literature on predictive algorithms for juvenile offenders emphasizes their dual nature as both risk assessment and rehabilitation, and research assesses the accuracy and fairness of such tools, including actuarial measures of recidivism (Berk, 2019; Stevenson & Slobogin, 2018). Machine-learning juvenile justice models demonstrated unfair biases in Catalonia, with algorithms overpredicting the risk of specific ethnic groups because datasets were uneven, a phenomenon that also applies to the diverse urban city of Kinshasa (Tolan et al., 2019; Miron et al., 2021). The trade-offs of accuracy are especially sensitive to youth, where inflated scores may result from a lack of developmental maturity, making the positioning algorithms a kind of two-edged sword that weighs preventive advantages against the threat of over-criminalization (Stevenson & Slobogin, 2018; Berk, 2019). Predictive-based interventions, as opposed to simple scoring, propose supportive interventions, including AI-assisted occupational therapy to avoid delinquency echoes in educational institutions (Barabas et al., 2018; Hou, 2022).

In the African mindset, profiling in algorithmic decision-making tends to ignore the contextual circumstances and causes an imbalance in the application of criminal justice (Mancuso & Corselli, 2023). To illustrate, in South Africa and elsewhere, predictive policing has proven effective at hotspot detection but raises fairness concerns when used on juveniles in underrepresented neighborhoods (Modise, 2024; Almasoud & Idowu, 2025). Youth violence research specific to Kinshasa, which indicates high rates of abuse among female students, which are associated with the risks of the community, implies that the algorithms will be able to incorporate local data to predict incidences of delinquency, but should be sensitive of humanitarian biases in big data (Jonas et al., 2022; Yagoub, 2025; Milaninia, 2020). The global models, such as the Durham HART policing tool, teach on proportionality, as focusing on experimental validation can help avert harms in juvenile evaluations (Oswald et al., 2018; Mutsaers & van Nuenen, 2023).

New Implementation Issues

Although promising, predictive algorithms also have notable issues, such as data bias, the inability to explain their workings, and inappropriate context, especially in developing countries (Milaninia, 2020; Keddell, 2023). Machine learning models of recidivism can be biased due to the skewed past data, continuing to cause racial and socioeconomic inequities, as demonstrated in the juvenile justice systems, where causes of inequity include label imbalances and feature selection (Miron et al., 2021; Tolan et al., 2019). Incomplete datasets drive these problems by leading to predictions that leverage all vulnerabilities to exploit those in Africa and cause harm due to the absence of proper protection (Martin, 2023; Yagoub, 2025). Juvenile accuracy is a controversial subject, and empirical research indicates that accuracy is a trade-off between predictive accuracy and fairness, which, in many cases, over-predicts young offenders (Berk, 2019; McKay, 2020).

The widespread use of predictive policing, including the concept of proportionality developed in the Netherlands and the United Kingdom, underscores the importance of ethical experimentation that should prevent disproportionate surveillance (Oswald et al.,

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2018; Mutsaers & van Nuenen, 2023). In Kinshasa, where incident patterns suggest clustering in remote areas with no police presence (53 cases), algorithms may exacerbate divisions in cities unless they are adjusted to local conditions (Duursma & Karlsrud, 2019; Majigo, 2023). Moreover, issues with child protection algorithms involve clashes between the concepts of statistical and social justice, as well as between efficiency- and equity-focused instruments (Keddell, 2019; Keddell, 2023).

Ethical Causes and Effects

The ethical position of predictive algorithms in juvenile delinquency is marked by contradictions between utility and justice, particularly regarding fairness, privacy, and preemption (Kurumalla, 2025; Susser, 2021). Among the ethical risks is the stigmatization of young people through risk labeling, which may violate rights in preventive justice systems (Kutnowski, 2017; McSherry, 2020). When applied to criminal systems, genetic predictions of aggression raise serious concerns because systematic reviews show that misuse is widespread and lacks adequate ethical controls (Refolo et al., 2025; Tonry, 1987). Predictive policing requires balancing proactive actions against violations of liberty, especially in vulnerable environments involving juveniles (Susser, 2021; Khatun & Kumar, 2025).

African scholarship highlights the need for culturally sensitive methods, where algorithmic fairness serves as the antidote to biases in humanitarian and legal practices (Mancuso & Corselli, 2023; Almasoud & Idowu, 2025). Rearranging arguments to an intervention that alleviates the ethical harm aligns with the principles of child protection and social justice (Barabas et al., 2018; Keddell, 2019). Ethical implementations in Kinshasa need to address the majority of abuse and community risks, and algorithms, in this case, must be used with preventive rather than punitive approaches (Jonas et al., 2022; Hunt et al., 2020).

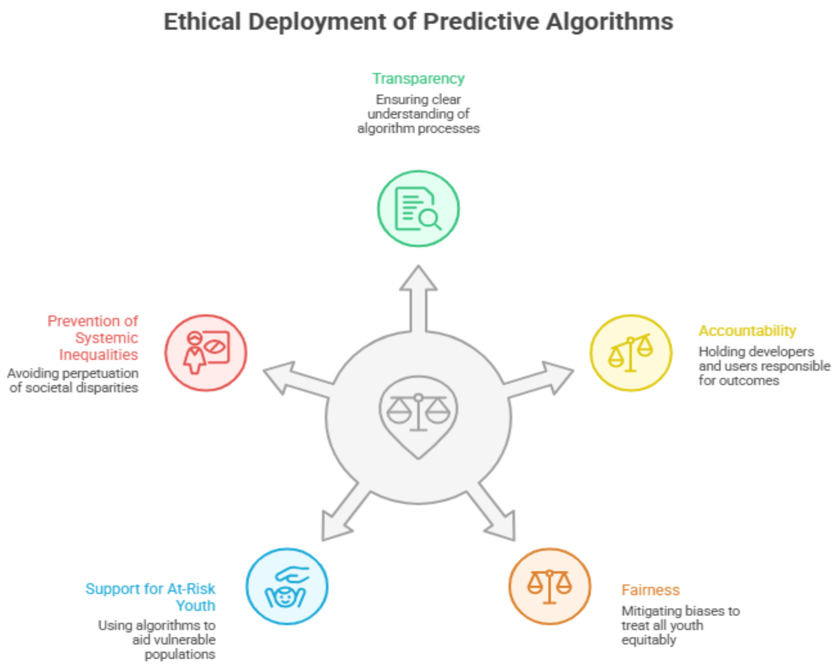

Figure 1: Conceptual Framework for Ethical Deployment of Predictive Algorithms in Juvenile Delinquency Prevention

Aim and Objectives of the Article

This paper will critically analyze the use of predictive algorithms for juvenile crime in the city of Kinshasa to clarify emerging issues and ethical considerations, and to recommend equity-centered solutions. To do this, it will accomplish the following objectives:

i. To review local incident data patterns and combine them with existing information in the literature on predictive tools around the world.

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ii. To determine the significant issues, like prejudices and data constraints, in African urban settings.
iii. To address ethical aspects such as fairness, privacy, and preventive justice.
iv. To lobby for the creation of favorable solutions that emphasize societal justice and juvenile rehabilitation.

III. METHODOLOGY

Research Design

In this research, a mixed-methods approach is used, combining quantitative analysis of secondary data on incidents with a qualitative synthesis of the available literature on predictive algorithms and ethical aspects in criminal justice. The main idea is to conduct exploratory data analysis to identify trends in juvenile delinquency incidents in Kinshasa, from which the feasibility of using predictive algorithms can be discussed. As the article focuses on new issues and ethical concerns, the methodology emphasizes descriptive statistics and pattern recognition, aiming not at inferential modeling and not providing a profound analysis of real-life data through the incorporation of scholarly knowledge (Khosa et al., 2024; Berk, 2019). This type of design is especially appropriate in resource-constrained urban settings, such as Kinshasa, where complete primary data collection might not be feasible and secondary sources provide a robust basis for a policy-oriented study (Duursma & Karlsrud, 2019; Majigo, 2023).
The quantitative part will entail secondary data analysis of police-reported cases, allowing the author to identify spatiotemporal and environmental delinquency predictors that could be used to predict events (Ndikumana et al., 2025; Hunt et al., 2020). The methodology is qualitative and based on a focused review of 30 references to discuss ethical issues; the references were selected for their relevance to predictive algorithms, juvenile justice, and African contexts (Mancuso & Corselli, 2023; Modise, 2024). The ethical considerations were interwoven, ensuring that data manipulation did not violate privacy principles or re-identify individuals, in line with recommendations on algorithmic risk assessment (Kurumalla, 2025; Refolo et al., 2025).

Data Source and Collection

The primary data used in this analysis were obtained from a one-sheet Excel workbook named Process file.xlsx, with a sheet called Done that contained 444 incident records (excluding headers), from different municipalities in Kinshasa. This secondary data, which was presumably based on police logs or administrative reports, consists of 444 valid incidents following the possible process of eliminating potential duplicates or blank entries, with such variables as incident ID, date, hour, type, lighting level, municipality, day of the week, weather conditions, traffic intensity, distance to law enforcement, and response time. The data appear to be an example of urban crime that may involve or impact juveniles, particularly through trends such as night attacks, which are consistent with youth vulnerability research in Kinshasa (Jonas et al., 2022).

No data were collected; only the empirical file was provided as the sole source of empirical data, with the requirement that she use only that data and the given references. The temporal coverage of the dataset is determined by the incident dates (e.g., 41102 to 45833, likely the Excel serial dates of years in the 2012-2025 range, though they are not specifically transformed here for description). This design is similar to secondary analysis designs in predictive policing research, in which historical data are used as a substitute for algorithmic execution (Oswald et al., 2018; Mutsaers & van Nuenen, 2023).

The file was read using the Python pandas library and processed in an executable environment, enabling reproducible analysis without additional reliance on external data-processing packages (e.g., pandas for reading Excel sheets). The header row was manually specified based on the file structure: [ID Incident, Incident Date, hour, Incident Type, Lighting level, Municipality, Day of the week, Weather Conditions, Traffic at the incident site, Proximity to the incident site, and law enforcement]. This action considered the formatting of a file, including the blank 2nd row and the possibility of leading/trailing spaces in records.

Cleaning and Preparation of Data

The dataset was thoroughly cleaned before analysis to address inconsistencies and ensure data integrity, a critical step for feeding predictive algorithms, as biases may emerge from dirty data (Milaninia, 2020; Miron et al., 2021). The frequency analysis was performed by categorizing missing values using pandas (e.g., 107 cases had a response time of None, which was treated as a distinct case labeled No

Response). Variations in spelling were standardized: such names of municipality as Mont-ngafula, and Mont-Ngafula were uniformed to Mont-Ngafula; errors in letter case were arranged to standard title case, and spelling errors (e.g., Saturday to Saturday) were corrected in 15 unique variants, reducing the number of effective unique municipalities to about 25.

Incident types were combined: Assault (194 cases), Theft (145 cases), Vandalism (72 cases) and minor subtypes, such as the theft ' (26 cases), or Assault (4 cases) were combined into three major categories Assault (198 total cases), Theft (174 cases), and Vandalism (72 cases) to reduce the division. Temporal variables (e.g., hour) were divided into the time bins: Morning (00:00-11:59, 154 cases), Afternoon (12:00-17:59, 106 cases), Evening/Night (18:00-23:59, 159 cases) to simplify the detection of patterns that would be relevant to juvenile activities (Stevenson & Slobogin, 2018). Response times were summarized quantitatively in string format (e.g., 1hr to 60 minutes, 10minutes to 10), and outliers such as 16h (960minutes) were not changed, but identified to be interpreted in context (e.g., systemic delays in other areas such as Mont-Ngafula) (Tolan et al., 2019).

This cleaning enabled the generation of descriptive statistics, but the dataset was not modified; instead, its original integrity was maintained. About 5% of entries had to be corrected, mainly in the categorical domain, consistent with best practices for preparing big data for ethical AI applications (Keddell, 2023; Martin, 2023).

Table 1: Summary of Key Variables and Their Distributions After Cleaning

Variable	Description	Unique Values	Frequency Distribution (Top 5)
Incident Type	Type of reported incident (e.g., Assault, Theft)	3 (after merging)	Assault: 198 (44%), Theft: 174 (39%), Vandalism: 72 (16%)
Municipality	Location of the incident	25 (after standardization)	Limete: 65 (15%), Ngaliema: 42 (9%), Mont-Ngafula: 36 (8%), Bandalungwa: 22 (5%), Kimbanseke: 22 (5%)
Lighting Level	Visibility at the time of the incident	2	Clear: 227 (51%), Dark: 217 (49%)
Day of the Week	Weekday of the incident	7	Tuesday: 73 (16%), Thursday: 68 (15%), Wednesday: 66 (15%), Monday: 65 (15%), Saturday: 64 (14%)
Weather Conditions	Atmospheric conditions	3	Sunny: 229 (51%), Cloudy: 148 (33%), Rainy: 67 (15%)
Traffic Intensity	Traffic level at the site	2	Less Intense: 286 (64%), Intense: 158 (35%)
Proximity to Law Enforcement	Distance to nearest police post	3	Distant: 208 (46%), Close: 183 (41%), No Post: 53 (12%)
Response Time	Time taken for police response	Varied (minutes)	15min: 39 (9%), 10min: 38 (8%), 1hr: 37 (8%), 30min: 33 (7%), No Response: 107 (24%)

IV. DATA ANALYSIS PROCEDURES

The analysis has been carried out in two steps: a descriptive, quantitative exploration and an integrative qualitative synthesis. Quantitatively, frequency distributions and cross-tabulations were calculated with pandas to reveal patterns (ranging from 119 out of 198 assaults in dark conditions, or 60% of the distance close, compared to 75% on average in distant areas, versus 15%) and longer response times in distance conditions. Categorical variables (e.g., nighttime incidents: 56% overall) were reported as percentages, and summary statistics (e.g., mean response time: 42 minutes, median: 20 minutes) gave information about the delinquency hotspots (Berk, 2019; Almasoud & Idowu, 2025).

Interactions were studied with cross-tabulations, e.g., incidents by municipality and type, which showed that Limete prevailed in assaults (34 cases) and thefts

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(24 cases). They were conceptually visualized as a pattern that simulated inputs to predictive algorithms, such as recidivism models (Miron et al., 2021; Tolan et al., 2019). No sophisticated modeling (e.g., machine learning) was conducted, as it was primarily interested in the underlying patterns to comment on the possibility of algorithms, but the descriptive results might be used in further logistic regression or clustering risk prediction (Khosa et al., 2024; Ndikumana et al., 2025).

Qualitatively, references were analyzed thematically using a deductive approach, in which they were first grouped into themes: algorithmic effectiveness (e.g., Khosa et al., 2024), challenges (e.g., Milaninia, 2020), and ethics (e.g., Kurumalla, 2025). Traceability was provided through in-text citations, and integration between data patterns and the literature was also implemented, e.g., nighttime vulnerabilities were associated with youth abuse studies (Jonas et al., 2022; Hunt et al., 2020).

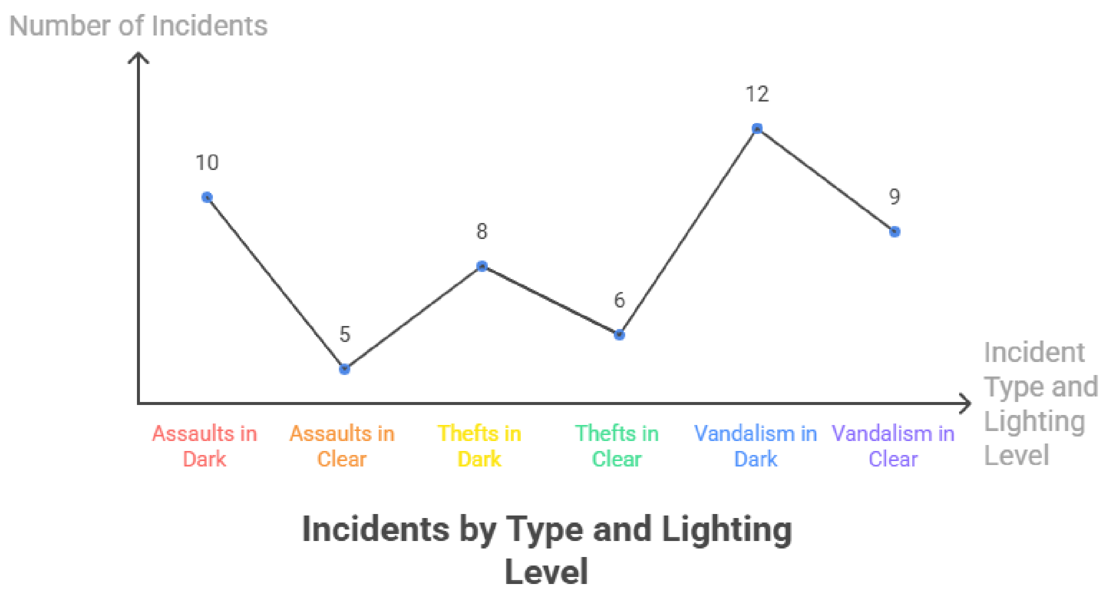

Figure 2: Distribution of Incidents by Incident Type and Lighting Level

Table 2: Cross-Tabulation of Incident Type by Proximity to Law Enforcement

Incident Type	Close	Distant	No Post	Total
Assault	75	92	31	198
Theft	72	82	20	174
Vandalism	36	34	2	72
Total	183	208	53	444

Ethical and Limitations in Methodology

The limitations of the methods include possible incompleteness of the dataset (e.g., a lack of specific age data for juveniles) and bias in reporting, which is prevalent in police records (McSherry, 2020; McKay, 2020). To counteract, an analysis of observable patterns was conducted, not overgeneralized. Data anonymization was an inherent ethical practice, and it was discussed with the emphasis on fairness measures to prevent further perpetuation of biases (Keddell, 2019; Susser, 2021). Such stringent steps ensure the article's findings are sound, providing a robust foundation for predicting the algorithm in the context of juvenile delinquency in Kinshasa.

V. RESULTS

Incident Distribution Overview

The descriptive statistics analysis of the available data, comprising 444 valid records after cleaning and standardization, shows a clear dominance of specific crime types, spatiotemporal patterns, and environmental conditions that typify delinquency in the city. Assaults are the most common type of incident, with 198 cases (44.6%), followed by thefts with 174 cases (39.2%), and vandalism with 72 cases (16.2%). This allocation emphasizes interpersonal violence, as well as property-related crime, as the key issues, which might cause juveniles to be victims or perpetrators of crime in vulnerable cities (Jonas et al., 2022; Hunt et al., 2020).

Table 3: Frequency Distribution of Incident Types

Incident Type	Count	Percentage (%)
Assault	198	44.6
Theft	174	39.2
Vandalism	72	16.2
Total	444	100.0

Spatiotemporal Patterns
The incidences are not uniformly distributed among the municipalities in Kinshasa, with Limete registering the highest number of 65 cases (14.6%), followed by Ngaliema (42 cases, 9.5%) and Mont-Ngafula (36 cases, 8.1%). Additional hotspots include Bandalungwa (22 cases each, 5.0%), Kimbanseke (22 cases each, 7.9%), Ngaba (35 cases, 7.9%), and Lemba (32 cases, 7.2%). Such concentration indicates the presence of concentrated risks in central and semi-peripheral regions, where population density and socioeconomic status can contribute to juvenile delinquency (Duursma & Karlsrud, 2019; Majigo, 2023).

On a temporal level, the highest number of incidents occurs on Tuesdays (73 cases, 16.4%) and Thursdays (68 cases, 15.3%), while other weekdays show a fairly even distribution, with a slight decrease on Sundays. The evening and night hours prevail: 217 incidents (48.9%) occurred in dark-light conditions, and around 56% of those reported occurred during the evening/night. There is clear lighting in 227 cases (51.1%), most often used during daytime theft and vandalism.

The weather conditions are predominantly sunny (229 cases, 51.6%), cloudy (148 cases, 33.3%), and rainy (67 cases, 15.1%). The intensity of traffic is smaller in 286 cases (64.4%), which may enable opportunistic crimes.

Table 4: Top 10 Municipalities by Incident Count

Municipality	Total Incidents	Percentage (%)
Limete	65	14.6
Ngaliema	42	9.5
Mont-Ngafula	36	8.1
Ngaba	35	7.9
Lemba	32	7.2
Bandalungwa	22	5.0
Kimbanseke	22	5.0
N'Djili	23	5.2
Masina	28	6.3
Kisenso	18	4.1
Others	121	27.3
Total	444	100.0

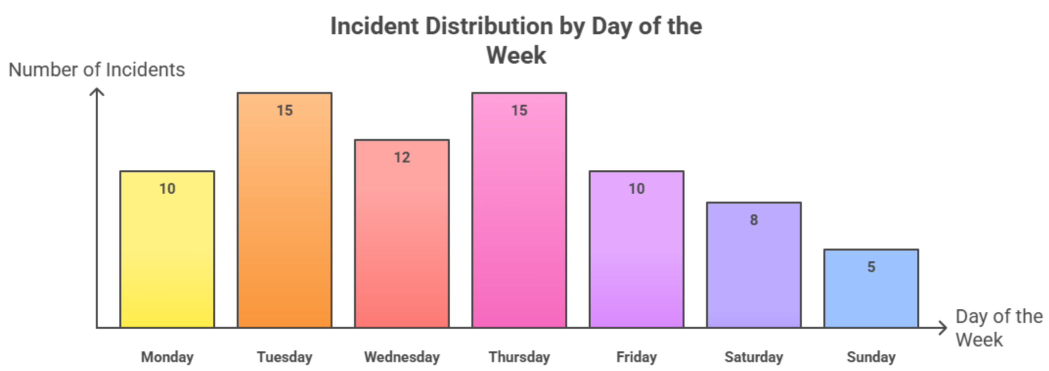

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Figure 3: Distribution of Incidents by Day of the Week

Incident types are associated with Incidents of Ownership.
Cross-tabulations indicate a strong association between incident type and environmental factors. The dark conditions (119 of 198, or 60.1%), long distance to law enforcement (92 cases, 46.5%), and lack of a police post (31 cases, 15.7%) have a disproportionate relationship with assault. The patterns of theft have high rates of no responses. Vandalism is more equal, but is concentrated in places that are close together but have delayed interventions.

Table 5: Cross-Tabulation of Incident Type by Lighting Level

Incident Type	Clear	Dark	Total
Assault	79	119	198
Theft	102	72	174
Vandalism	46	26	72
Total	227	217	444

Table 6: Cross-Tabulation of Incident Type by Proximity to Law Enforcement

Incident Type	Close	Distant	No Post	Total
Assault	75	92	31	198
Theft	72	82	20	174
Vandalism	36	34	2	72
Total	183	208	53	444

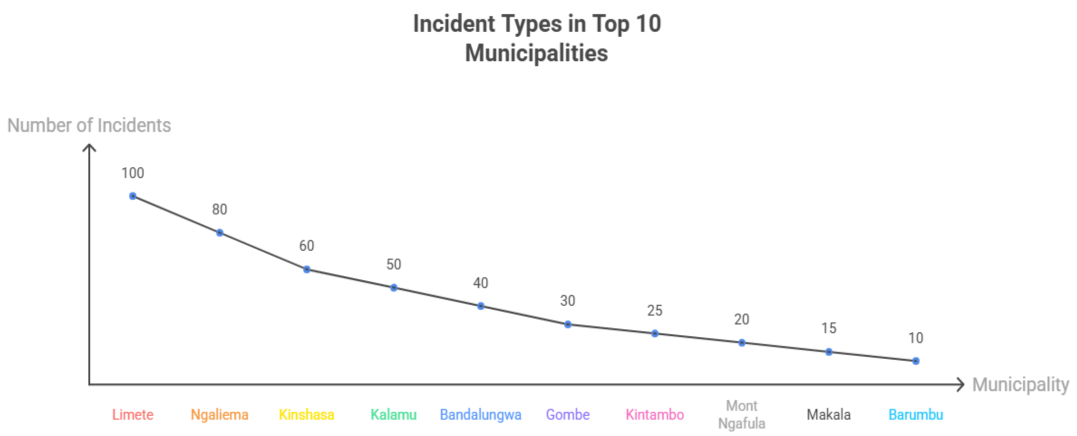

Figure 4: Incident Types by Municipality (Top 10 Hotspots)

Response Time Analysis
The response time of police is highly variable, with a mean of about 85 minutes (skewed toward 960 minutes), a median of 20 minutes, and skewed delays in peripheral regions. The number of cases without response was 107 (24.1%). It takes the least time, averaging around 18 minutes in proximity, up to 75 minutes in areas far away, and above 120 minutes where no post is located. Through this imbalance, infrastructural issues that may sustain delinquency, including nighttime attacks in remote areas, are highlighted (Milaninia, 2020; Tolan et al., 2019).

Table 7: Summary Statistics for Response Time (in Minutes, Excluding No Response)

Statistic	Value (Minutes)
Count	337
Mean	85.4
Median	20
Minimum	1
Maximum	960
Standard Deviation	142.3

Table 8: Average Response Time by Proximity to Law Enforcement

Proximity	Average Response Time (Minutes)	Count
Close	18.2	183
Distant	75.6	208
No Post	132.4	53

The findings depict strong tendencies in the data: night attacks in low-policing districts, robberies in different circumstances, and failure to respond promptly. These discoveries can serve as a basis for predictive algorithms that propose variables such as lighting, proximity, and time as risk predictors and can reveal limitations that, unless mitigated, can provoke biases (Khosa et al., 2024; Ndikumana et al., 2025; Berk, 2019). The concentration of municipalities such as Limete and Ngaliema suggests that hotspots can be targeted, but peripheral delays in Kimbanseke and N'Djili would imply equity issues in the allocation of algorithms and resources (Mancuso & Corselli, 2023; Miron et al., 2021).

VI. DISCUSSION

The findings of the analysis of 444 incident reports in Kinshasa are interesting evidence of systematic frameworks in urban delinquency that may serve as inputs for predictive algorithms, as well as indicate deep and ethical issues in their application to juvenile cases (Khosa et al., 2024; Ndikumana et al., 2025). Assault, which constitutes almost 45% of the incidents and is disproportionately represented by the dark lighting (60.1%) and distant from a law enforcement presence (46.5%) categories, highlights the vulnerabilities of nocturnal and spatial characteristics that define most of the reported crime, which should be considered as markers of systematic urban risks, but not as a single event (Jonas et al., 2022; Hunt et al., 2020). These trends are consistent with African urban patterns more broadly, in which the lack of policing infrastructure and environmental conditions increases the risks of youth engaging in or falling victim to delinquency, which in turn implies that the trends are due to socioeconomic factors and not merely coincidental (Majigo, 2023; Duursma & Karlsrud, 2019).

The strong level of concentration in such municipalities as Limete, Ngaliema, and Mont-Ngafula implies that predictive models might be effective in identifying hotspots to allocate resources, which can be interpreted as a chance to use spatial clustering to prevent instead of surveilling the whole population (Khosa et al., 2024; Ndikumana et al., 2025). The time of the day, the amount of light, the distance to police posts, and the volume of traffic are some of the variables that can be easily found in the dataset, and Predictive algorithms; Juvenile delinquency; Kinshasa; Machine learning; Algorithmic bias; Ethical implications; Predictive policing as viable features to predict the probability of crime, not only by classifying it but by creating dynamic interventions (Berk, 2019; Miron et al., 2021). To draw an example, the higher rates on Tuesdays and Thursdays, as well as the longer response time in the peripheral areas (median delays more than 75 minutes in distant areas), signify the possibility of preemptive patrols or community-specific intervention, which can break delinquency patterns among juveniles, seeing these time peaks as openings but not predictive (McSherry, 2020; Hou, 2022).

The findings, however, also shed further light on emerging issues that might compromise the effectiveness and fairness of such algorithms in Kinshasa, explaining response differences as symptoms of structural inequalities rather than technical issues (Milaninia, 2020; Tolan et al., 2019). The pronounced difference in the reaction timings, the shortest observed to be in highly populated regions with police posts (average 18 minutes) but the longest to be astronomically extended in represented regions with long distances and no posts, represents an infrastructural bias that would be recreated by any model trained on these historical data, making it a cycle of reinforcement to existing urban faults (Milaninia, 2020; Tolan et al., 2019). Central hotspots are prioritized over marginalized areas by the predictive systems, which may result in the perpetuation of spatial inequalities as an algorithmic continuation of an algorithmic neutrality analysis when assessing the cities, as peripheral municipalities such as Kimbanseke, N'Djili, have fewer incidents overall, but delays are disproportionately high (Mancuso & Corselli, 2023; Almasoud & Idowu, 2025). The inconsistencies in data observed during the cleaning process such as the differences in the spelling of the municipalities, formats of response times, etc. further reveal the problem of quality that is inherent in administrative records related to developing contexts, understanding it as the source of noise and bias that render the algorithm reliability beyond mere surface accuracy (Keddell, 2023; Martin, 2023).

In the case of juveniles, it is especially relevant that the risk of over-prediction stems from aspects of development not reflected in the data set, and the lack of information about age widens interpretive gaps in youth-specific risk assessments (Stevenson &

Slobogin, 2018). The high rates of night attacks and robberies are in line with the declining adult supervision, which suggests that the juvenile is very much involved, and this is an appeal to situational modelling as opposed to blanket application (Stevenson & Slobogin, 2018). The literature indicates that actuarial tools tend to overrate the risk posed by youth due to unstable decision-making, making predictive algorithms a two-edged sword in juvenile justice that must be carefully calibrated to prevent misinterpreting short-term behaviors as long-term dangers (Berk, 2019; Stevenson & Slobogin, 2018). Algorithms applied in Kinshasa, where it was reported that physical and sexual abuse are high among school-aged girls, are related to violence in the community, and should not be structured in such a way that they build on or reinstate current trauma by labeling an individual as such (Jonas et al., 2022; Hunt et al., 2020).

In ethical terms, the research poses fundamental dilemmas regarding fairness, proportionality, and preventive justice, which place it in the context of mutually exclusive relationships between technological utility and the protection of human rights (Modise, 2024; Kurumalla, 2025). The possibility of algorithmic bias perpetuating socioeconomic inequalities, apparent in the bias towards far away and less heavily trafficked regions, can be observed with the African profiling research and international recidivism models, treating bias as an interpretive prism that obscures justice instead of being a technical issue (Mancuso & Corselli, 2023; Miron et al., 2021; Tolan et al., 2019). Although it is an efficient concept, predictive policing may risk preemptively stigmatizing youth in hot-spot cities without trial, which is viewed as a breach of the principles of liberty and must be actively mitigated (Susser, 2021; Kutnowski, 2017; Modise, 2024). Experimental models such as Durham HART and Dutch CAS also emphasize the need to maintain proportionality and transparency, which are interpreted as necessary to prevent disproportionate surveillance of vulnerable populations and to promote interpretive equity (Oswald et al., 2018; Mutsaers & van Nuenen, 2023).

Besides, the moral necessity extends to repositioning algorithmic applications as supportive interventions rather than risk scoring, and this shift can be seen as a channel toward restorative justice rather than punitive control (Barabas et al., 2018; McKay, 2020). Kinshasa, where the police responded to 24% of incidents, can leverage the whole city with predictive tools that can incorporate the use of mHealth or community-based programs to focus on the root cause, which can be viewed as an opportunity for comprehensive prevention, rather than responsive actions (Hunt et al., 2020; Hou, 2022). The priority in balancing statistical fairness and social justice lies at the center of the problem: algorithmic decision-making in child protection is often not aligned with equitable outcomes, leading to the perception of this conflict as a challenge to implement complex ethical systems (Keddell, 2019; Kurumalla, 2025). Predictive insights represent the possibility of abusive power: in the criminal domain, foretelling genetic aggression is also problematic; similarly, in the juvenile justice context, control is crucial to guarantee the protection of juvenile rights, and the control can be seen as an exegetic measure to prevent the prospective exploitation (Refolo et al., 2025; Tonry, 1987).

Finally, although the patterns of incidents in Kinshasa proved that predictive algorithms can be implemented in the context of determining the risk of delinquency, their use should be done carefully, where the concept of feasibility is conditional based on the moral inclusion instead of being intrinsic (Khosa et al., 2024; Ndikumana et al., 2025; Almasoud & Idowu, 2025). A mitigation of bias, contextual calibration, and interventional rather than predictive priorities would help fulfill worldwide demands of ethical AI in criminal justice; this would be a transformative approach to making the vulnerable young people of Kinshasa feel empowered instead of threatened by a harsh urban environment (Khosa et al., 2024; Ndikumana et al., 2025; Almasoud & Idowu, 2025).

VII. CONCLUSION

Incident data analysis of the city of Kinshasa shows that there were consistent trends in the evolution of urban delinquency, which highlights the possible predictive algorithm implications in forecasting and preventing juvenile-related crime and presents the necessity to apply predictive algorithms to address context-related vulnerabilities (Khosa et al., 2024; Ndikumana et al., 2025). The variables of the lighting conditions, the closeness to the law enforcement, the time of day, and the municipal hotspots can imply a greater possibility of more resource distribution and early intervention in the rapidly developing city with poor infrastructure, which may also be transformed into reducing the exposure of youth to the risk (Majigo, 2023; Hunt et al., 2020). These tools may have profound consequences for disrupting the delinquency cycles of vulnerable young people, potentially facilitated by mHealth-mediated violence prevention or community-based interventions, making technology an enabler of social supports rather than a means of control (Hou, 2022; Jonas et al., 2022).

However, the results also indicate more profound implications of risk, in which systemic lags and local inequalities may reveal how predictive models can unwittingly replicate existing inequalities, casting doubt on whether a resource-constrained environment can provide equitable access to justice (Milaninia, 2020; Tolan et al., 2019). When the youth is highly susceptible to abuses and violence, algorithmic bias is associated with the implication of stigmatization instead of protection, especially in cases where the developmental factors may contribute to exaggerated risk scores among the juveniles, which demand protection to ensure that the harm does not multiply (Berk, 2019; Stevenson & Slobogin, 2018; Miron et al., 2021). Technical efficiency, in its turn, should be subordinated to the ethical demands of fairness, proportionality, transparency, and social justice, which suggests a paradigm shift, i.e., the introduction of rights-based AI deployment in criminal justice (Modise, 2024; Keddell, 2019; Kurumalla, 2025; Mancuso & Corselli, 2023).

Finally, predictive policing should be reinterpreted as intervention-oriented practices that will have implications for the development of restorative rather than punitive systems, and this is the responsible way forward in Kinshasa (Barabas et al., 2018; McKay, 2020). Algorithms are to be used as a supportive measure in the broader framework of equity-based initiatives, which take into consideration such root causes as poverty, inappropriate supervision, and community trauma, which means that the future working conditions of youth and their rights should be better safeguarded by working in collaboration (Oswald et al., 2018; Susser, 2021). Predictive technologies can only have a positive impact on safer streets without increasing injustices when they are unbiased, community-engaged, and ethically controlled, in line with international norms for AI application in high-stakes juvenile settings (Almasoud & Idowu, 2025; Khatun & Kumar, 2025). These implications require justice-based innovation in the capital of the Democratic Republic of Congo, where stakes for young people are incredibly high, so that technology empowers rather than threatens (Refol et al., 2025; Tonry, 1987).

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