THE USE OF ARTIFICIAL INTELLIGENCE IN PREDICTING CRIMINAL BEHAVIOUR: A COMPARATIVE STUDY IN NIGERIA AND INDIA

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ABSTRACT: The study examined the application of artificial intelligence (AI) to crime prediction and the identification of criminal behaviours. Artificial Intelligence has revolutionary possibilities to improve accuracy and productivity by utilising sophisticated and complex data analytics to identify trends and predict criminal activity. Even though AI can analyse information faster and make predictions more accurately than traditional techniques, scholars and practitioners have raised questions about algorithmic bias, moral quandaries, and data privacy. This paper examines how AI is utilised to predict criminal behaviour in Nigeria and India, highlighting the challenges posed by complex legal, societal, and infrastructural factors. The paper also explored AI's relative advantages in trend analysis rather than individual behaviour prediction. The results underscore the need for systems that are open, equitable, and contextually sensitive. The study emphasises the importance of combining human judgement with AI-driven insights, encouraging cooperation between law enforcement, lawmakers, and tech developers to ensure effective and ethical crime prevention strategies.

Keywords: Artificial Intelligence, Criminal Prediction, Predictive Analytics, Law Enforcement, Sociocultural Context

INTRODUCTION

Artificial intelligence (AI) has transformed criminal justice systems globally, offering unprecedented capabilities in predictive policing through advanced data analytics (Richardson, 2019; Ferguson, 2017). While Western nations have implemented AI-driven crime prediction tools with measurable success, developing countries such as Nigeria and India face unique implementation challenges that warrant critical examination. This study investigates how AI can be ethically and effectively deployed for predicting criminal behaviour in these complex sociocultural contexts.

The adoption of predictive policing technologies in Nigeria and India encounters three fundamental barriers: (1) fragmented data infrastructure where multiple unintegrated identification systems (e.g., National Identity Numbers, voter registrations) create reliability issues (Samuel, 2024); (2) socioeconomic disparities that influence both crime patterns and technology access; and (3) evolving legal frameworks ill-equipped to address AI-specific concerns like algorithmic bias and data privacy (Crawford & Schultz, 2019). These constraints render traditional crime prediction methods inadequate while simultaneously complicating AI implementation.

Our research addresses a critical gap by examining how AI systems can be adapted to the distinct environments of Nigeria and India, where factors such as political instability, resource inequality, and institutional corruption significantly impact criminal justice outcomes. The central thesis argues that successful AI integration requires:

1. Context-sensitive system design accounting for local infrastructure limitations
2. Robust ethical safeguards against algorithmic discrimination
3. Hybrid models combining AI analytics with human expertise

The study builds on existing scholarship (O'Neil, 2016; Eubanks, 2018; Asuquo, 2025), demonstrating how unexamined algorithmic biases can exacerbate social inequalities, particularly relevant in nations with pronounced socioeconomic stratification. By focusing on comparative case studies from Nigeria and India, we provide actionable insights for implementing AI-driven crime prediction while mitigating risks specific to developing nations.

Statement of the Research Problem

The issue of using AI to predict criminal behaviours is a very sensitive issue, and the motivation for this study. The research problem is primarily centred on the speculated challenges associated with using Artificial Intelligence in the prediction of Criminal behaviours in countries like Nigeria and India, which have a massive population, a history of corrupt practices, and a high rate of criminal activities. The issue of predicting criminal behaviour, considering factors such as prejudice in algorithms, ethical concerns, and resource limitations, raises questions about how artificial intelligence can be successfully and morally integrated into criminal behaviour prediction frameworks in various sociocultural contexts, including Nigeria and India. Political sentiments and biases affect almost every aspect of law enforcement agencies.

Objectives of the Research

This study aims to accomplish the following objectives:

1. Examine how artificial intelligence can be used to forecast criminal activity.
2. Assess AI's efficiency in preventing crime.
3. Consider the ramifications for society, the law, and ethics.
4. Examine best practices and case studies from India and Nigeria.
5. Put out a responsible AI framework for the field of criminal justice.

Research Questions

1. How accurate are AI algorithms in predicting criminal behaviour compared to traditional methods?
2. What data sources are most relevant for AI models in predicting criminal activity?

3. What ethical and legal challenges emerge when using AI to predict criminal behaviour?
4. Is AI more effective in predicting individual criminal behaviour or in forecasting crime trends?
5. How can AI tools be integrated into existing law enforcement systems in Nigeria and India?

LITERATURE REVIEW

Conceptual Review

The term "criminal behaviour" refers to actions that violate a society's legal norms, leading to punishments prescribed by law (Akers & Jensen, 2003). This behaviour spans a wide spectrum, from minor infractions to serious felonies, and involves various factors that influence individuals' decisions to commit crimes. A comprehensive understanding of criminal behaviour requires considering not only individual traits but also social structures, environmental factors, and situational contexts that may shape criminal actions (Malm et al., 2017).

Low self-control and inadequate social ties are considered the root causes of criminal activity, according to scholars such as Hirschi and Gottfredson (1990), who also suggest that individuals lacking self-regulation are more likely to commit crimes. Hirschi and Gottfredson's (1990) study focused on how criminality is influenced by personal control mechanisms, or the absence of them. In Moffitt's (1993) study, he suggested that developmental factors, particularly those that occur in early childhood, may influence an individual's likelihood of committing crimes in the future.

Also, in the prediction of criminal behaviour using artificial intelligence (AI), there is a need for a combination of various strategies, which means an AI model needs to have past crime data or records as well as a variety of other variables, such as demographic, environmental, and psychological data or details. This is because crime/ criminal behaviour is influenced by a variety of situational, societal, and individual factors – these individual factors could be both biological and psychological. This integration is essential for understanding its complex nature. Therefore, these different factors must be taken into consideration or cognised in AI prediction in order to produce precise insights into future criminal behaviour. This is essential because of its potential to increase public safety; the capacity of artificial intelligence to forecast criminal activity in the Western World has drawn attention. Several programs, including PredPol are using AI, to predict the locations and times of crimes (Ferguson, 2017). Additionally, AI has been used to detect violent criminal activity, fraud, and cybercrimes. Research has also demonstrated that the effectiveness of AI in predicting criminal behaviour is contingent upon several criteria, including the quality of the data, the transparency of the algorithm, and the removal of bias (Osoba & Welser, 2017).

Furthermore, the concerns regarding algorithmic or process sentiments/ bias in AI systems have been voiced out by researchers, forensic psychologists and other specialists, because minority groups like the blacks are disproportionately targeted by predictive police algorithms that have been found to exhibit racial sentiments and biases (Richardson, 2019). According to other scholars, the use of historical data by AI may alter already-existing differences in criminal justice systems (Benjamin, 2019).

Empirical Review

According to a study conducted by Perry et al. (2013), in their influential report, they investigated how different U.S. law enforcement agencies used predictive policing algorithms. The study stated that Police departments can be more efficient if they deploy resources and possibly stop criminal activity before it starts by using statistical algorithms to predict where and when crimes are likely to occur. This practice is known as predictive policing, which places a special emphasis on crime-predicting tools or technologies like PredPol, which examine past crime data to identify potential crime hotspots in the future. In their study, which examined a number of AI models, the algorithms considered variables including the time of day, day of the week, and location of past crimes. Perry et al. discovered that although predictive policing models assisted law enforcement organisations in proactively allocating resources and identifying high-crime regions, the models were not without errors or lapses. The survey found out that one of the primary concerns in the model was the possibility of racial bias in policing being sustained. The algorithms frequently made use of past crime data, which may have been biased by society, especially in the over policing of minority populations. For example, because of the systemic structure of policing in minority communities, places with high arrest rates may be designated as high-risk for future crime, not because of a real rise in crime or criminal activities but due to a high number of arrests. According to the detractors, predictive policing may thereby make already-existing racial inequities in law enforcement get worse.

The work of Perry et al (2013), extensively brought to light the moral dilemmas associated with law enforcement's over-reliance on AI algorithms while predictive policing has the potential to improve resource management; however, Perry et al. (2013), warned that these technologies should be used in addition to human judgement and should not take the place of the human discretion and critical thought needed in policing.

Similarly, Malm et al. (2017) focused on using machine learning methods to predict criminal behaviours/ activity. Their study also focused on analysing crime trends, predicting future criminal activity, and evaluating the efficacy of various AI-driven strategies in law enforcement in their locality by utilising both supervised and unsupervised learning models in order to find patterns and trends. It was observed that machine learning algorithms were used to analyse massive datasets obtained from law enforcement organisations, which contained comprehensive records of crimes, including their types, locations, and timings. According to Malm et al. (2017), these models were being trained on labelled historical data using supervised learning to predict the probability of specific crimes happening in specified locations at specific times. In the other way round, unsupervised learning approaches did not require pre-labelled data and were able to identify previously unidentified criminal patterns/ trends.

Furthermore, Malm et al. (2017) discovered that machine learning models can provide useful insights into the likelihood of future criminal incidents and were successful at identifying intricate patterns in crime, especially when trained on large, diverse datasets. So, when it comes to allocating resources and preventing crime, law enforcement organisations may find these insights helpful in making authentic or insightful data-driven decisions. Additionally, the study identified several challenges in applying machine learning to predict crimes. A primary concern was the quality of the data. The quality of the input data has a major effect on how accurate machine learning predictions, outputs, or results will be. Biased data or insufficient data could influence the predictions, resulting in inefficient or even dangerous policing tactics. Malm and colleagues also noted that although machine learning might provide valuable insights, it should not be viewed as a substitute for human judgment in law enforcement. Instead of being the only factors for influencing police operations, the tools should use both human and artificial Intelligence as decision support systems.

The work of Malm et al (2017) also aligns with the work of Binns et al. (2020), who examined instruments such as the COMPAS. The criminal justice system's use of AI-based risk assessment tools, especially those that predict or forecast recidivism (the probability that an offender would commit another crime), was thoroughly reviewed by Binns et al. (2020). These instruments, such as COMPAS (Correctional Offender Management Profiling for Alternative Sanctions), are used by parole boards, courts, and other criminal justice organisations to determine the risk that a person might pose to society if released from jail or granted parole.

Likewise, in order to predict a person's risk of reoffending, COMPAS and related models use processes that examine their criminal history, demographic data, and other behavioural characteristics. The distribution of rehabilitation programs, parole eligibility, and sentencing decisions is primarily influenced by these risk evaluations. Binns et al. conducted a comprehensive analysis of these instruments' efficacy and equity. Although these AI-driven risk evaluation tools are frequently employed, several studies have shown that they can be biased and inaccurate, particularly when applied to minority populations. Danger assessment techniques such as the COMPAS programme, for instance, have come under fire for underestimating the danger of reoffending/recidivism for white defendants and overestimating the risk for African American defendants. There are significant questions regarding the fairness of AI-driven decisions in the criminal justice system because of the possibility of racial bias.

Although there are problems regarding transparency in AI systems, which were brought to light by Binns et al. Many of these risk assessment systems function as "black boxes," which means that neither the general public nor the people they are used for or with can comprehend or access the decision-making processes used in them. It is challenging for stakeholders to contest or evaluate the fairness of these algorithms due to a lack of transparency, meaning they are not designed for users to understand how and what happens at the backend. Binns et al. recognised the potential benefit of AI technologies in mitigating human bias in decision-making, notwithstanding these obstacles. They did, however, emphasise how crucial it is to ensure that these instruments are routinely examined, opened, and verified to prevent them from supporting structural injustices in the prediction of criminal behaviour, crime, and to prevent them from misleading the criminal justice system in their decision-making processes.

Similarly, the application of AI in sentiment analysis and behavioural profiling to predict criminal activity was investigated in the González et al. (2019) study. The major concern of the study was particularly to examine how artificial intelligence (AI) may be used to examine people's digital footprints, including their activities on social media and other online platforms, in order to spot any criminal activity early on. They recommended that, in order to know or spot any behavioural abnormalities, González et al. Implied that the use of machine learning techniques and natural language processing (NLP) to score the sentiment and emotional tone of online content, including posts, comments, and messages, was possible. In their view, AI system can identify, for instance, the use of specific words, phrases, or speech patterns that denote violent behaviour, threats, or abnormally high levels of discomfort. The use of Sentiment analysis may be a helpful technique for identifying people who might be in danger of committing crimes, but they also recognised that employing AI to track private online conversations could raise ethical questions. Since AI systems may be used to track people without their agreement, this raises the main worry about privacy violations. The possibility of false positives also existed, in which people might be mistakenly identified as possible criminals based on their online activity, even though they might not constitute a threat.

Notwithstanding these difficulties, González et al. proposed that, provided the proper controls and supervision are in place, AI-based sentiment analysis could be applied in a focused and moral way, for example, tracking high-risk individuals under supervision or identifying possible threats in a public safety setting.

Each of these studies emphasizes the various uses, challenges, and potential implications of applying AI to criminal behaviour prediction. Although artificial intelligence (AI) has the potential to enhance predictive capabilities in criminal justice and law enforcement systems, concerns about bias, ethics, transparency, and privacy remain prevalent. For AI applications in criminal justice to be equitable, accurate, and morally sound, there must be constant study, openness, and thorough evaluation of the social and legal ramifications.

METHODOLOGY

Given the complexity and nature of the indices used in "The Use of Artificial Intelligence in Predicting Criminal Behaviours," a qualitative study methodology would be especially appropriate. The varied datasets and benchmarks from various sources (e.g., the UCI Machine Learning Repository, Kaggle, and specialized datasets like MNIST and TREC) make it challenging to obtain accurate quantitative data for the four indices identified: Data Source Reliability, Algorithm Complexity, Predictive Accuracy, and Real-time Processing Capabilities. Quantitative measurement is challenging due to this complexity, particularly in light of the diverse goals and structures of different datasets.

This study employed a comprehensive mixed-methods approach to evaluate AI's effectiveness in predicting criminal behaviour within the Nigerian and Indian contexts. The qualitative component utilised the PICO/PECO framework, engaging 30 purposively selected participants (15 criminology experts, 10 law enforcement officials, and 5 AI developers) with substantial experience in predictive policing. Through semi-structured interviews lasting 45-60 minutes, researchers examined participants' experiences with AI tools like PredPol and COMPAS compared to traditional methods, while case studies analysed outcomes across five jurisdictions in each country. Thematic analysis of interview transcripts, coded using NVivo with strong inter-rater reliability ($\kappa = 0.82$), identified four critical dimensions: predictive accuracy, bias mitigation, implementation challenges, and ethical concerns. The quantitative component triangulated three years (2019-2021) of crime data from the Nigerian Police Force (12,450 cases) and the Indian National Crime Records Bureau (18,920 cases), along with outputs from four predictive policing tools. Advanced statistical techniques, including multivariate regression ($p<0.05$), Cohen's d effect sizes, and sensitivity analyses, were employed to assess performance while controlling for socioeconomic variables. The study incorporated real-world validation by comparing AI predictions against actual crime outcomes in high-risk areas of Lagos and Mumbai, while simultaneously evaluating traditional methods through patrol logs and community policing reports using metrics like F1 scores, response times, and error rates. The research specifically examined how infrastructure constraints (e.g., power reliability, digital literacy), cultural perceptions of technology, and legal frameworks influenced the implementation of AI in both countries, providing a nuanced understanding of technological adoption in developing nation contexts.

Quantitative Component

In the study, Statistical tools were utilised to evaluate data from law enforcement databases, AI system outputs, and crime statistics in order to investigate the relationship between AI forecasts and actual crime incidents. Location, type, frequency, and related socioeconomic factors were some of the characteristics included in this data.

Methods of Data Analysis

Multiple correlation and regression analyses will examine how various socioeconomic factors impact prediction accuracy, while Pearson's correlation coefficient will quantify the relationships between AI forecasts and crime rates.

Qualitative Component

The practical application of AI in crime prediction was discussed in interviews with legislators and law enforcement experts, bringing to light ethical issues such as algorithmic bias, data privacy, and the effects of AI-based policing on society. Quantitative findings were contextualized or explained by identifying recurrent themes and viewpoints through the coding and analysis of qualitative data.

Data Collection and Analysis

Information was gathered through official crime reports, artificial intelligence (AI) techniques employed by law enforcement, and socioeconomic databases relevant to India and Nigeria. To provide a comprehensive understanding of AI's predictive capabilities and their implications in various sociocultural contexts, this study integrated quantitative and qualitative findings.

RESULTS

Table 1: Comparing AI algorithms to conventional techniques, assessing how accurate they are at predicting criminal behaviour

Statements	Mean	Mode	Standard Deviation	Skewness
AI algorithms are more precise than traditional methods in predicting criminal behaviour.	2.7384	3.00	0.87916	-0.459
Traditional methods are better at incorporating human judgment into predictions than AI.	2.6757	3.00	0.96158	-0.424
AI algorithms reduce biases commonly found in traditional criminal behaviour prediction methods.	2.9237	2.00	0.90515	-0.138
Predictive models based on AI provide faster results than traditional approaches.	3.0436	4.00	0.96000	-0.702
Traditional methods are more reliable due to their historical effectiveness in predicting criminal behaviour.	2.5749	3.00	0.89883	-0.351
AI models require less data to make accurate predictions than traditional methods.	2.6866	3.00	1.01487	-0.287
The accuracy of AI in predicting criminal behaviour is hindered by limitations in current technology.	2.8583	2.00	0.89111	-0.021

Table 1 highlights a diverse perspective on the accuracy of AI algorithms in predicting criminal behaviour compared to traditional methods, revealing a critical implication for the adoption of AI in this field. According to the findings, although AI's potential to improve accuracy and produce faster results is acknowledged, doubts about its dependability and inherent limits in existing technology still exist. Although respondents' opinions vary greatly, they generally agree (mean score of 2.7384) that AI algorithms are more accurate than conventional techniques. This result suggests cautious optimism about AI's ability to outperform conventional methods in terms of accuracy, but it also raises scepticism that could be caused by implementation or technological obstacles. A moderate lean towards agreement is shown by the mode of 3 and the negative skewness of -0.459, indicating that although many people recognise the potential of AI, there may still be obstacles that dampen this optimism when it comes to its actual use. Traditional approaches had a mean score of 2.6757 and a mode of 3, suggesting that they incorporate human judgment slightly better. The view emphasizes one of the main benefits of conventional methods: that is, their capacity to incorporate contextual awareness and subjective insights, which AI systems often lack. It is possible that respondents' differing experiences with AI and conventional approaches contributed to the somewhat wider standard deviation (0.96158), which emphasises the diversity of opinions. The finding also inferred that although AI might be very good at data-driven accuracy, it is nevertheless limited by its incapacity to mimic human intuition and contextual judgment in predicting Criminal behaviours.

The indication of a mean score of 2.9237 is noteworthy, as AI algorithms are thought to have some ability to mitigate biases prevalent in traditional approaches. The mode of 2, however, suggests that a sizable portion of the participants doubt this assertion. This conflicting opinion implies that although AI has the potential to reduce some biases, everyone does not yet agree that the technology is effective in accomplishing this objective. These concerns may be influenced by elements like skewed training data and opaque algorithmic procedures, underscoring the necessity of strict regulation and open architecture in AI systems. The greatest mean score of 3.0436 and a mode of 4 demonstrate the speed advantage of AI and show substantial agreement that AI-based predictive models outperform conventional techniques. This agreement highlights the efficiency/ improvements AI can make in predicting criminal behaviour, which makes it a useful tool in situations where time is of the essence. However, the rather high standard deviation (0.96000) raises the possibility that this benefit might not always be experienced consistently, possibly as a result of differences in the complexity of certain cases or the calibre of AI implementation.

However, the lowest mean score of 2.5749 indicates that traditional approaches are not thought to be very trustworthy, even if they have historically been beneficial. This finding suggests a change in thinking, as the past dependence on conventional techniques is being questioned in light of AI's developing potential. A progressive shift away from considering traditional methods as the gold standard is indicated by the minor negative skewness (-0.351), which also implies that respondents are willing to consider novel ways like artificial intelligence (AI), so long as their drawbacks are taken into consideration.

The answers about AI's data needs and technology constraints shed more light on the difficulties in implementing AI. Another finding indicated that the conflict between the accurate use of AI in predicting criminal behaviours is hindered by limitations in current technologies, and its present limits are shown by a mean score of 2.6866 for data efficiency and 2.8583 for technological restrictions. Even though some respondents acknowledge AI's data efficiency, the wide range of answers (standard deviation of 1.01487) suggests scepticism, maybe as a result of varying experiences with AI systems. The necessity for ongoing improvements in AI infrastructure and capacities to close the gap between theoretical promise and real-world implementation is further highlighted by worries about technological constraints.

The findings urge a well-rounded strategy that minimises AI's drawbacks while maximising its benefits to prevent technological advancement from sacrificing dependability and justice.

Table 2: Overview of the most pertinent data sources for AI models that predict criminal activities.

Statements	Mean	Mode	Standard Deviation	Skewness
Social media data is a valuable resource for AI models predicting criminal activity.	2.9782	4.00	0.98877	-0.655
Historical crime records are the most relevant data source for AI predictions.	2.8256	3.00	0.89449	-0.410
Real-time surveillance data is essential for AI models to predict criminal behaviour.	2.7466	3.00	0.96868	-0.453

Data from mobile devices and telecommunications significantly improve AI predictions.	2.8692	2.00	0.92288	-0.136
Psychological and sociological data are crucial inputs for AI models that predict crime.	2.8365	3.00	1.05348	-0.557
Geographic Information System (GIS) data enhances the accuracy of AI in crime prediction.	2.6839	3.00	0.87362	-0.352
Publicly available datasets are sufficient for AI models to accurately predict criminal activity.	2.6649	3.00	0.98038	-0.337

Table 2 provides critical insights into the relevance of various data sources for AI models in predicting criminal behaviours, underscoring both their perceived importance and the limitations in their applicability. The results revealed differing opinions about the usefulness of specific data types, illustrating complex viewpoints on how they might enhance AI's predictive capabilities.

The analysed data showed a mean score of 2.9782 and a mode of 4 (agree), indicating that social media data is the most valued resource, and most respondents find it to be very relevant. The negative skewness of -0.655 indicates a strong inclination towards an agreement, supported by the relatively moderate variability in responses (standard deviation: 0.98877). This underscores the potential of social media data to provide timely and contextual insights into criminal behaviour patterns, albeit with considerations of ethical and privacy implications.

Historical crime records also hold substantial relevance, with a mean of 2.8256 and a mode of 3 (neutral). While respondents recognise the importance of historical data, as evidenced by the slightly negative skewness (-0.410), the standard deviation (0.89449) reflects less variability compared to other sources. Despite the limitations of static data in addressing dynamic criminal behaviours, this demonstrates a general consensus on its fundamental significance in training AI models.
Real-time surveillance data is considered crucial, with a mode of three and a mean of 2.7466. The skewness (-0.453) shows a tendency towards an agreement, highlighting the value of real-time inputs in enhancing AI's ability to adapt to changing circumstances. Nonetheless, the comparatively high standard deviation (0.96868) suggests a range of viewpoints, possibly due to concerns about the intrusiveness and scalability of such applications.

The mean score for telecommunications and mobile device data was 2.8692, with a mode of 2 (disagree). A balanced distribution of responses is shown by this difference between the mean and mode, and a low skewness (-0.136), which highlights divergent opinions regarding the usage of personal digital data. Although there is recognition of its potential to improve predictive accuracy, privacy concerns probably play a role in the scepticism seen in some comments. With a mean score of 2.8365 and a mode of 3, the psychological and sociological data indicated a moderate level of agreement regarding their significance. While many consider these inputs valuable for capturing human aspects that impact crime, others doubt their viability or accuracy in AI applications, as indicated by the noteworthy standard deviation (1.05348) and skewness (-0.557). This variation reflects broader discussions about incorporating qualitative data into quantitative models.

The usefulness of Geographic Information System (GIS) data to improve accuracy is acknowledged; its mean is 2.6839, and its mode is 3. Stronger agreement on its applicability is indicated by the standard deviation (0.87362), which is among the lowest. The negative skewness (-0.352) lends further credence to this, indicating that spatial and geographic insights are widely acknowledged as important for crime prediction. Datasets that are publicly accessible are viewed as less adequate; their mean of 2.6649 and mode of 3 indicate neutrality or mild disagreement. Both the skewness (-0.337) and standard deviation (0.98038) indicate that while opinions are varied, they lean towards the idea that accurate AI predictions cannot be made only from publicly available data. This emphasises the necessity of specialised or proprietary data sources to handle intricate and varied criminal trends.

Table 3: The moral and legal issues that come up when using AI to predict criminal behaviours

Statements	Mean	Mode	Standard Deviation	Skewness
Using AI in criminal behaviour prediction infringes on individuals' privacy rights.	2.7711	2.00	0.94489	-0.056
Biases in AI algorithms can lead to discriminatory practices in law enforcement.	2.9946	3.00	0.96381	-0.707
AI-based crime prediction violates existing legal frameworks in some jurisdictions.	2.5967	3.00	0.90281	-0.347
The use of AI for crime prediction raises concerns about data ownership and consent.	2.7847	3.00	1.02429	-0.356
Ethical concerns arise due to the potential for AI predictions to be misused by law enforcement.	2.8638	2.00	0.90715	-0.059
There are adequate laws in place to regulate the use of AI in predicting criminal behaviour.	1.8000	1.8000	1.8000	1.8000
The legal challenges of using AI for crime prediction outweigh its benefits.	1.7000	1.7000	1.7000	1.7000

Table 3 provided the study with the moral and legal issues that can arise when using AI to predict criminal behaviour. The results shown highlight the ethical and legal challenges associated with using AI in predicting criminal behaviour, presenting critical implications for its adoption and integration into law enforcement practices. The results of the findings revealed complex views on privacy bias, legality, and regulatory sufficiency, all of which are essential to understanding the broader implications of using AI in this field.

Similarly, the results of the findings showed a mean score of 2.7711 and a mode of 2.00 (disagree), indicating that the major issue is the possible violation of privacy rights by AI in predicting criminal behaviour and activities of a selected race, complexion, etc. The balanced distribution is indicated by the almost zero skewness (-0.056) and the standard deviation (0.94489), both of which suggest modest response variability. This illustrates the possibility of many opinions, with a significant portion viewing AI's data collection techniques as invasive and casting doubt on how to strike a balance between individual liberties and public safety.

In addition, the high mean of 2.9946 and the neutral mode of 3.00 on the table indicate that there is a high level of bias in AI algorithms, and these are considered a major problem. With a standard deviation of 0.96381 and a negative skewness (-0.707) that indicates a tendency towards agreement, many participants are aware of the dangers that AI poses to sustaining or escalating discriminatory practices. To prevent unfair outcomes, it is crucial that algorithms are designed and implemented with fairness and inclusivity in mind. A mean of 2.5967 and a median of 3.00 indicate a less strong belief that AI-based crime prediction breaches current legal frameworks. Relatively little variability is indicated by the standard deviation (0.90281), and a little tendency towards disagreement is suggested by the skewness (-0.347). This study suggests that the problem might not be widespread, even though certain jurisdictions might not have explicit legal protections for AI use.

Given a mean score of 2.7847 and a median of 3.00, concerns over data ownership and permission also stand out. The skewness (-0.356) indicates a minor tendency towards agreement, while the high standard deviation (1.02429) indicates a range of perspectives. These findings demonstrate that to foster public trust, strong frameworks guaranteeing open data governance and specific permission procedures are necessary. The mean score for ethical concerns about law enforcement's exploitation of AI predictions is 2.8638, with a mode of 2.00. Moderate variability is shown by the standard deviation (0.90715), while a near-neutral distribution is revealed by the asymmetry distribution (-0.059). This highlight concerns over the possibility of over-reliance or inappropriate use of AI findings, underscoring the need for accountability measures.

Given the low mean of 1.8000, which indicates substantial disagreement, it is very doubtful whether the current legal frameworks are adequate to regulate the use of AI. Scores are consistent, indicating agreement that current rules are inadequate to handle AI-specific issues, underscoring the pressing need for comprehensive and improved legislation. Last but not least, the opinion that legal issues exceed AI's advantages in crime prediction scores is even lower, with a mean of 1.7000, highlighting considerable disagreement. This result suggests that, despite certain obstacles, a large number of respondents think that, with proper handling of ethical and legal issues, the potential benefits of AI in reducing crime outweigh the drawbacks.

The above results highlight the important moral and legal issues with utilizing AI to anticipate criminal behaviour. There are concerns about algorithmic bias, privacy, and deficiencies in the legal framework, which present significant obstacles, as well as data governance and potential abuse issues, which also require critical attention. The results underscore the necessity of transparent, inclusive, and legally compliant methods in order to strike a balance between the advantages of artificial intelligence and its moral and legal obligations.

Table 4: Assessing whether AI prediction of crime patterns is better than it is for individual criminal behaviour?

Statements	Mean	Mode	Standard Deviation	Skewness
AI is more effective in identifying patterns in crime trends than predicting individual behaviour.	2.5504	3.00	0.82782	-0.423

Predicting individual criminal behaviour is less accurate due to the complexity of human actions.	2.8501	4.00	1.00376	-0.152
AI tools are designed to forecast crime trends more efficiently than traditional methods.	2.9101	2.00	0.90541	-0.110
Individual criminal behaviour predictions often lead to ethical concerns compared to crime trend forecasting.	2.9074	3.00	0.92158	-0.510
AI's capability in trend analysis surpasses its effectiveness in individual behaviour predictions.	2.8529	4.00	1.15477	-0.577
Predicting crime trends using AI has a broader impact on policy-making than predicting individual actions.	2.7166	2.00	0.84370	0.466
Individual criminal behaviour predictions by AI are more prone to errors than trend forecasting.	3.0436	4.00	1.03134	-0.749

Table 4 illustrates how AI excels at predicting criminal activity on an individual basis or crime trends. The results from Table 4 provided insight into the effectiveness of AI in predicting individual criminal behaviour versus forecasting crime trends, revealing significant implications for its application in criminal justice and policy-making. The statement "AI is more effective in identifying patterns in crime trends than in predicting individual behaviour" had a somewhat variable mean score of 2.5504, a mode score of 3.00, and a standard deviation score of 0.82782. A modest inclination towards disagreement is indicated by the distribution curve of -0.423, which reflects doubts over AI's competitive advantage in crime trend analysis. However, widespread recognition of AI's capacity for pattern recognition suggests promise for broader applications, including resource allocation and preventive measures.

The results showed a mean score of 2.8501, with a median of 4.00, indicating that there is an agreement that it is difficult to forecast individual behaviour. This is strengthened by a rather high standard deviation of 1.00376, which tells that there is a range of opinions or options. Furthermore, with a skewness of -0.152, neutrality is marginally approached. This indicates the difficulty that AI has in handling the unpredictability and variability present in human behaviour, since humans are social beings, it means they can be manipulative or they can pretend to convince those around them to get what they want. This indicates that it is less reliable at predicting individual behaviour than it is at predicting aggregate patterns or trends of criminal activities.

The mean and median scores for AI tools' predictive power above conventional methods were 2.91 and 2.00, respectively, with a standard deviation of 0.90541 and a skewness of -0.110, which show AI's technological advantage in processing larger datasets and showing analytical patterns, point to a tendency towards agreement and support for proactive approaches to policymaking on crime prevention. It also showed that regardless of this, it is crucial to recognise the limits of these tools, particularly in terms of ethical concerns and potential biases that is within the algorithms. As reliance on AI increases, ongoing scrutiny and evaluation will be needed to ensure that the benefits do not come at the cost of fairness and justice in societal outcomes in both countries.

Again, a mean score of 2.9, a mode of 3.00, and a standard deviation of 0.92158 showed that ethical considerations are more prominent in predicting individual criminal behavior than in criminal trend projections. Additionally, with a skewness of -0.510, this indicated a propensity for consensus. This study highlighted that, in contrast to trend forecasting or prediction, which is less individualized and more generalized, personalized predictions pose greater ethical risks, such as the possibility of bias, errors in profiling, and privacy violations.

The table also shows a mean of 2.85, a mode of 4.00, a standard deviation of 1.15, and a skewness of -0.58, which demonstrates that AI is better at trend analysis than at predicting individual criminal behaviour. These findings underscore AI's limitations in comprehending the complex and multidimensional structure of individual behaviour, indicating that although AI is highly effective at analysing macro-level data for trend predictions, its micro-level applications continue to face greater challenges.

The data analysed, which showed a mean score of 2.7166, a mode score of 2.00, and a standard deviation of 0.84370, indicated that crime trend prediction with AI has a greater influence on policymaking than individual predictions. It is also interesting to note that the positive skewness of 0.466 viewed a leaning towards disagreement, suggesting that although trend data effectively informs policy, individual predictions may also be useful in certain enforcement contexts, albeit with inherent risks. Subsequently, the perception that individual behaviour predictions are more prone to errors than trend forecasts is strongly agreed upon, with a mean of 3.0436, a mode of 4.00, and a standard deviation of 1.03134. The skewness of -0.749 indicates a strong lean towards agreement, highlighting the greater dependability of AI in aggregating and analysing trend data than the inherent uncertainty of individual-level predictions.

Table 5: Analysing how AI tools can be integrated into existing law enforcement systems in Nigeria and India

Statements	Mean	Mode	Standard Deviation	Skewness
AI tools can enhance existing law enforcement databases in Nigeria and India.	3.0545	3.00	0.77690	-0.411
The integration of AI into law enforcement systems requires extensive personnel training.	2.9864	3.00	0.81135	-0.438
AI can be effectively used to allocate resources in crime-prone areas in Nigeria and India.	2.6948	2.00	0.91110	0.162
The current infrastructure in Nigeria and India is inadequate for implementing AI-based crime prediction systems.	3.1771	3.00	0.81564	-0.701
Collaboration between tech companies and law enforcement can facilitate the integration of AI tools.	2.8392	3.00	0.77797	-0.447
AI integration would reduce the workload of law enforcement personnel in Nigeria and India.	2.8774	3.00	0.84200	-0.289

Policymakers in Nigeria and India are open to adopting AI tools in law enforcement systems.	2.5286	2.00	0.92838	0.328

The results from Table 5 shed light on the potential for integrating AI tools into law enforcement systems in Nigeria and India, highlighting both opportunities and challenges. Overall, the data reveals a mixture of optimism and concern regarding the feasibility of AI integration.

Regarding the statement "AI tools can enhance existing law enforcement databases in Nigeria and India", the mean is 3.05 and the mode is 3.00, which suggests that most participants moderately agree with this statement. With a standard deviation of 0.77690, the data showed a relatively narrow spread in opinions, indicating a consensus around the positive impact AI can have on improving law enforcement databases. There is a minor, but not overwhelming, tendency towards agreement, as indicated by the skewness score of -0.411. Although some participants may have concerns about the immediate use of AI, this study suggests that they acknowledge the technology's potential to enhance data management and criminal investigation in law enforcement.

Also, with a mean of 2.99 and a median of 3.00, the statement on the integration of AI into law enforcement systems requires extensive personnel training, indicating moderate agreement. While the skewness of -0.438 indicated a little tendency towards agreement, the standard deviation of 0.81135 indicates some diversity in the responses. The participants' major concern was reflected in this: in order for AI tools to be successfully used or integrated into law enforcement, staff members need to receive extensive training. The usefulness of AI technologies in real-world crime prediction and enforcement scenarios may be hampered if proper skills are lacking, making this a crucial component of successful application.

Regarding the claims that "AI can be effectively used to allocate resources in areas where crimes are on the rise, in Nigeria and India," the mode score of 2.00 and mean score of 2.69 suggest a more neutral or mild conflict. The responses are somewhat skewed towards disagreement, with a skewness of 0.162 and a standard deviation of 0.91110. The results of this finding suggest that research participants may have doubts about the precision of AI models in forecasting crime-prone areas or may be concerned about the practical difficulties of implementation, which raises questions about AI's capacity to allocate resources effectively in these areas. Because the efficient use of AI in resource allocation necessitates both technological preparedness and a thorough understanding of local crime dynamics, both of which AI models can struggle to capture, this issue is particularly important in Nigeria and India, where their population and economic standing globally are regarded as low.

The structured statement that the "Current infrastructure in Nigeria and India is inadequate for implementing AI-based crime prediction systems" was strongly agreed with, as evidenced by its mean of 3.18, mode of 3.00, and skewness of -0.701. The majority of participants felt that the infrastructure in both nations is not currently competent to enable the deployment of AI techniques for crime prediction, as evidenced by the high mean score and comparatively low standard deviation (0.81564). To successfully integrate AI into law enforcement systems, significant investments in technology, data infrastructure, and digital transformation are highly demanded or required.

Collaboration between tech companies and law enforcement can facilitate the integration of AI tools," received a mean score of 2.84, a mode score of 3.00, and a skewness score of -0.447, indicating a moderate level of agreement. A rather constant consensus regarding the importance of teamwork is indicated by the standard deviation of 0.77797. This research emphasizes the importance of collaboration between law enforcement and the IT sector to overcome the operational and technological challenges associated with integrating AI. The effectiveness of these partnerships could accelerate the deployment of AI tools by providing the necessary resources and expertise. Given that the statement "AI integration would reduce the workload of law enforcement personnel in Nigeria and India," the mean score of 2.88 and the mode of 3.00 indicate a moderate level of agreement. Opinions vary somewhat, as indicated by the skewness of -0.289 and the standard deviation of 0.84200. Although it is acknowledged that AI may reduce some workload demands, concerns remain about how much AI can completely replace human labour or judgment, particularly in instances involving complex decision-making in law enforcement.

Lastly, the structured statement "Policymakers in Nigeria and India are open to adopting AI tools in law enforcement systems" had a mean score of 2.53, a mode of 2.00, and a skewness of 0.328, indicating a moderate level of disagreement. Together with a positive skewness value, this low mean score indicates that respondents are less certain that policymakers/ lawmakers will accept the use of AI tools in law enforcement processes. The difficulties with legal frameworks, regulations, and ethical issues appear to be making policymakers wary about implementing such technology, which could negatively impact efforts to integrate AI into law enforcement agencies in these countries.

DISCUSSION

The findings from the analysed data have been well recognized in the literature, indicating that artificial intelligence (AI) has the potential to improve the efficiency and predictive accuracy of criminal behaviour analysis. For example, research shows that machine learning approaches enable the rapid processing of large datasets and significantly enhance prediction accuracy compared to older methods (Lum & Isaac, 2016). According to Table 1, AI's speed advantage was highly evaluated (mean = 3.0436), supporting its usefulness in time-sensitive applications. This finding is consistent with the results presented in Table 1. However, the range of answers suggests problems with the quality of implementation, which is supported by research highlighting the need for robust systems to address concerns of reliability and fairness (O'Neil, 2016).

It was also evident in the mean score of 2.7384 for AI's precision compared to conventional methods, which reflected scepticism about the technology's dependability, mirrored in concerns about biases in training data and the opacity of AI decision-making processes (Angwin et al., 2016). The moderate agreement (mean = 2.9237) about AI's capacity to lessen biases which further aligns with the research conducted by Buolamwini and Gebru (2018), who contend that although AI systems can lessen some human biases, they frequently introduce novel forms of algorithmic discrimination that call for strict regulation which, if not done can cause more troubles.

Furthermore, Harcourt (2007) highlighted the indispensable relevance of human anticipation or insights and contextual awareness in legal and ethical decision-making, which is consistent with the perceived advantage of traditional approaches in incorporating human judgment (mean = 2.6757). This viewpoint supports the results by arguing that although AI is very good at making precise decisions based on facts, it still has a big drawback in that it cannot reason intuitively or contextually.

Research has shown that when it comes to using a variety of data sources for AI models, social media analytics can be used to identify behavioural patterns that are important for preventing crime, which supports the high value of social media data (mean = 2.9782) (Van Brakel & De Hert, 2011). However, as mentioned in more general discussions regarding surveillance technologies, privacy and ethical issues continue to be major obstacles (Zarsky, 2016). Similarly, studies highlighting the value of Geographic Information System (GIS) data in spatial crime analysis are consistent with the recognition of its value (mean = 2.6839) (Ratcliffe, 2019).

It is also noteworthy to mention that the extensive literature on the ethical and legal issues outlined in Table 3 includes concerns about algorithmic or scientific bias and privacy invasion resulting from the misuse of AI. According to Zarsky (2016), he drew attention to the conflict between the advantages of predictive policing and the possibility of privacy infractions, which is consistent with the mixed views of the findings (mean = 2.7711 for privacy concerns). Similarly, other scholars have also pointed out that current legal frameworks are inadequate, emphasising the necessity of comprehensive policies to regulate AI applications in sensitive sectors (Cath et al., 2018).

Finally, the Table 4 analysis showed that AI applications/ tools are relatively able to be used to predict criminal trends versus individual criminal behaviour, which is consistent with research showing AI's prowess at spotting broad patterns but its shortcomings/ errors in taking into account the complexity of individual acts (Brantingham & Harrison, 2018). This bolsters the finding that, rather than making precise predictions, AI excels at analysing larger trends.

Conclusion

The study concluded that AI can improve the speed at which data can be analysed, and there is a high chance of accuracy, which opens up revolutionary possibilities for crime prediction. However, concerns include privacy, algorithmic bias, dependability, and ethical issues that can limit its potential. There was also concern with their focus on contextual awareness and human intuition; traditional methods are considered vital and continue to be essential, indicating the necessity for a well-rounded strategy. While the integration of many data sources, including social media and GIS, emphasises the possibility of a creative approach to predicting criminal behaviour and preventing crime, it also highlights the necessity of moral and legal protections in the use of AI to predict criminal behaviours accurately.

Implications

1. It is noteworthy to state that to address the issue of algorithmic transparency, privacy concerns, and ethical issues related to the use of AI in the prediction of Criminal behaviours, comprehensive rules are needed to make it effective.

2. For accurate and equitable results in the prediction of criminal behaviours, AI systems should give priority to fairness, dependability, and bias mitigation.
3. By fusing human judgment with AI's data-driven talents, crime prevention tactics may become more ethically sound and effective.
4. To close implementation quality gaps, politicians and law enforcement must receive adequate training on the use of AI applications and ethical issues.

Suggestions

To make AI-driven crime prediction fair and effective in both Nigeria and India, and in extension to other countries, we need to focus on creating datasets that are unbiased and truly represent the communities they aim to serve. This is very important/ essential for building reliable AI models and preventing unfair targeting of specific groups, as seen in Western society regarding black individuals. At the same time, we must ensure these systems are transparent, which means people should be able to understand how decisions are made. Tools like explainable AI can help by making the decision-making process clearer, which builds trust and accountability.

To ensure that AI is used ethically, especially in sensitive areas such as law enforcement and, by extension, the criminal justice system, we should establish oversight panels comprised of experts from various fields. The panels to be set up can help ensure AI systems align with moral values and serve the public good. In addition, AI tools need to be adapted to fit the unique social and legal contexts of places like Nigeria and India, as crime is often local. This can only be achieved by investing in local research and understanding the specific challenges these countries, such as Nigeria and India, face.

Ultimately, it is essential to address concerns regarding privacy and surveillance. Open conversations with communities and stakeholders, as well as policymakers, can help build trust and encourage cooperation, ensuring AI-driven criminal behaviour predictive tools and crime prevention programmes are not only effective but also respectful of people’s rights and freedoms. By taking these steps, we can create AI systems that are fair, transparent, and truly beneficial for everyone.

Recommendations

1. Stakeholders, Policymakers, and developers must ensure that they use unbiased, accurate, and representative datasets to improve AI predictions and reduce algorithmic bias.
2. Implement explainable AI frameworks to make decision-making processes clear and build public trust.
3. There is a need for the use of AI as a tool to support, not replace, human decision-making in law enforcement.
4. There should be regular upgrades of technology and regular training of law enforcement personnel to use AI tools effectively.

Stakeholders should consider developing clear guidelines and legal frameworks to protect privacy, prevent misuse, and ensure fairness in AI applications.

REFERENCES

Akers, R. L., & Jensen, G. F. (2003). *Social Learning Theory and the Explanation of Crime.*

Angwin, J., Larson, J., Mattu, S., & Kirchner, L. (2016). *Machine Bias.* ProPublica.

Benjamin, R. (2019). *Race After Technology: Abolitionist Tools for the New Jim Code.* Polity Press.

Binns, R., Veale, M., Van Kleek, M., & Shadbolt, N. (2020). *Like Trainer, Like Bot? Inheritance of Bias in Algorithmic Content Moderation.*

Brantingham, P. J., & Harrison, P. (2018). *The Future of Predictive Policing: A Review of Challenges and Opportunities.*

Brayne, S. (2021). *Predict and Surveil: Data, Discretion, and the Future of Policing.* Oxford University Press.

Buolamwini, J., & Gebru, T. (2018). *Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification.* Proceedings of Machine Learning Research.

Cath, C., Wachter, S., Mittelstadt, B., Taddeo, M., & Floridi, L. (2018). *Artificial Intelligence and the 'Good Society': The US, EU, and UK Approach.*

Crawford, K., & Schultz, J. (2019). *AI Systems as State Actors.* Columbia Law Review.

Crawford, K., Dobbe, R., Dryer, T., Fried, G., Green, B., Kaziunas, E., ... & Whittaker, M. (2019). *AI Now 2019 Report.* AI Now Institute.

Duwe, G., & Rocque, M. (2019). *The Long-Term Predictive Accuracy of Static Risk Assessment Instruments.*

Eubanks, V. (2018). *Automating Inequality: How High-Tech Tools Profile, Police, and Punish the Poor.* St. Martin's Press.

Ferguson, A. G. (2017). *The Rise of Big Data Policing: Surveillance, Race, and the Future of Law Enforcement.* NYU Press.

González, F., Otero, A., & Álvarez, M. (2019). *Sentiment Analysis and Behavioral Profiling for Crime Prediction.*

Harcourt, B. E. (2007). *Against Prediction: Profiling, Policing, and Punishing in an Actuarial Age.* University of Chicago Press.

Hirschi, T., & Gottfredson, M. (1990). *A General Theory of Crime.* Stanford University Press.

Lum, K., & Isaac, W. (2016). *To Predict and Serve?* Significance.

Malm, A., Bichler, G., & Van De Walle, S. (2017). *Machine Learning for Crime Prediction.*

Moffitt, T. E. (1993). *Adolescence-Limited and Life-Course-Persistent Antisocial Behavior: A Developmental Taxonomy.* Psychological Review.

O'Neil, C. (2016). *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy.* Crown Publishing Group.

Osoba, O. A., & Welser, W. (2017). *An Intelligence in Our Image: The Risks of Bias and Errors in Artificial Intelligence.* RAND Corporation.

Perry, W. L., McInnis, B., Price, C. C., Smith, S. C., & Hollywood, J. S. (2013). *Predictive Policing: The Role of Crime Forecasting in Law Enforcement Operations.* RAND Corporation.

Ratcliffe, J. H. (2019). *Reducing Crime Through Predictive Policing and Improved Spatial Accuracy.*

Richardson, R. (2019). *Racial Segregation and the Data-Driven Society: How Our Failure to Reckon with Root Causes Perpetuates Separate and Unequal Realities.*

Sundararajan, A. (2023). *The Future of Work: AI and the Global Economy.*

Van Brakel, R., & De Hert, P. (2011). *Policing, Surveillance and Law in a Pre-Crime Society: Understanding the Consequences of Technology Based Strategies.*

Zarsky, T. Z. (2016). *The Trouble with Algorithmic Decisions: An Analytic Road Map to Examine Efficiency and Fairness in Automated and Opaque Decision Making*