East African Journal of Information Technology
eajit.eanso.org
Volume 7, Issue 1, 2024
Print ISSN: 2707-5346 | Online ISSN: 2707-5354
Title DOI: https://doi.org/10.37284/2707-5354

EAST AFRICAN NATURE & SCIENCE ORGANIZATION

Original Article

Criminology and Social Impact in The Age of Artificial Intelligence [AI]

Prof. John Ndikaru wa Teresia, PhD[1*]

[1] The Technical University of Kenya, P. O. Box 57173 - 00200, Nairobi, Kenya.
* Correspondence ORCID ID: https://orcid.org/0000-0001-88824-6352; Email: jndikaru@gmail.com

Article DOI: https://doi.org/10.37284/eajit.7.1.2141

Date Published:

26 August 2024

Keywords:

Bias and Discrimination, Regression Models, Safe City Project, Cybersex trafficking, Cybercrime, AI-Powered Tools, Predictive Policing, Algorithm, Crime Mapping.

ABSTRACT

The use of technology has permeated all facets of life, and brought about both positive and negative effects. Criminology as a fields has not been left behind and criminologists are developing various technological tools, including Artificial Intelligence (AI) models to use in detecting, managing and preventing criminal activities. This is a significant step considering that criminals have also found it convenient to use technology as a tool for perpetuating their activities. This paper focused on the adoption of AI in criminology, exploring the attendant benefits of its adoption; the negative social impact of its use and interventions that should be put in place to curb the negative ramification. Some of the beneficial use discussed in the paper include predictive policing, and crime risk assessment, which aids in preventing occurrence of criminal activities. However, the use of these AI models, while beneficial to these criminological functions have presented significant social implications, which include bias and discrimination that perpetuate social stereotypes; privacy breach that lead to the victimization of innocent people; opaque decision making that lead to distrust in the output by the AI tool; and unfair distribution of employment opportunities. The paper concluded that the adoption of AI in criminology is inevitable considering the digital era in which we are currently living in. However, while the benefit of the use of these technologies are varied and welcome, there is a need for ensuring that the legal, social and ethical concerns are adequately addressed. The paper, therefore, recommended the establishment of robust regulatory framework that guide the use of the AI models by law enforcement agencies; the integration of the use of the AI tools with human oversight; the inclusion and transparency and accountability in the operationalization of the tools; collaboration amongst the stakeholders. This paper has used recent extant literature to examine the intersection between criminology and social impact with respect to the use of Artificial Intelligence (AI).

APA CITATION

wa Teresia, J. N. (2024). Criminology and Social Impact in The Age of Artificial Intelligence [AI]. *East African Journal of Information Technology*, *7*(1), 221-239. https://doi.org/10.37284/eajit.7.1.2141

CHICAGO CITATION

wa Teresia, John Ndikaru. 2024. “Criminology and Social Impact in The Age of Artificial Intelligence [AI].”. *East African Journal of Information Technology* 7 (1), 221-239. https://doi.org/10.37284/eajit.7.1.2141.

Article DOI: https://doi.org/10.37284/eajit.7.1.2141

HARVARD CITATION

wa Teresia, J. N. (2024) "Criminology and Social Impact in The Age of Artificial Intelligence [AI].", *East African Journal of Information Technology*, 7(1), pp. 221-239. doi: 10.37284/eajit.7.1.2141.

IEEE CITATION

J. N. wa Teresia "Criminology and Social Impact in The Age of Artificial Intelligence [AI].", *EAJIT*, vol. 7, no. 1, pp. 221-239, Aug. 2024.

MLA CITATION

wa Teresia, John Ndikaru "Criminology and Social Impact in The Age of Artificial Intelligence [AI].". *East African Journal of Information Technology*, Vol. 7, no. 1, Aug. 2024, pp. 221-239, doi:10.37284/eajit.7.1.2141.

INTRODUCTION

The increased adoption of technology in all facets of life has not spared the field of criminology. Evidently, the integration of technology is criminology is credited for enhancing strategies for detecting, recording and addressing crime in its various aspects. Notably, criminals are using technology to advance their objectives as evident with the increased reported cases of cybercrime (Spivak & Shepherd, 2021). Criminologists, therefore, have had to respond in kind by using the same technology to advance their strategies to stay ahead of the criminals (Galič et al., 2022; Piraianu et al., 2023). However, the emergence and increased adoption of Artificial Intelligence (AI) has introduced significant paradigm shift with particular regard to the impact of crime and social impact (Meijer & Wessels, 2019; Piraianu et al., 2023; Spivak & Shepherd, 2021). Shamshi & Safei (2023) contends that AI present criminologists with both unprecedented opportunities and daunting challenges, thereby changing the nature of criminal behaviour, law enforcement approaches and societal responses in a fundamental way.

This paper acknowledged that criminals have advanced in their game and that in a bid to keep ahead of the authorities and their targets, they have adopted the use of AI in their activities. The increased adoption of technology use in almost all facets of life makes it viable for criminals to create crime scenes out of the digital space. However, this paper did not focus on perpetration of crime in the digital space using AI tools. The paper rather focused on the use of AI in aiding criminologists to do their work better and the potential social implications of the same.

THE USE OF ARTIFICIAL INTELLIGENCE IN CRIMINOLOGY

Recent extant literature reveal that AI is used in criminology in various ways, including predictive policing (Berk, 2021; Galič et al., 2022; Shad, 2023; Shamshi & Safei, 2023); risk assessment and decision-making (Berk, 2021; Dencik et al., 2019; Ezzeddine et al., 2023; Spivak & Shepherd, 2021; Thao, 2023); and victim identification and assistance (Awe et al., 2023; Dakalbab et al., 2022; Piraianu et al., 2023)

Predictive Policing

Criminologists have adopted AI use in several of their functions. For one AI has been increased used as a tool for detecting and investigating crime (Berk, 2021; Galič et al., 2022; Shad, 2023; Shamshi & Safei, 2023; Thao, 2023). In Vietnam, criminologist have adopted AI-powered tools such as risk assessment tools; data storage and linking tools and predictive analytics to detect and investigate crimes. The tools have proved invaluable with regard to expediting the detecting and investigation processes, thereby saving costs and time and end up yielding better outputs for the criminologists (Thao, 2023).

AI tools have also been credited for enhancing predictive policing in various contexts (Berk, 2021; Galič et al., 2022; Shad, 2023; Shamshi & Safei, 2023). Predictive policing is the use of data and algorithms to anticipate criminal activities (Shamshi & Safei, 2023) and is therefore, used by criminologists to come with strategic crime prevention approaches within particular contexts (Shad, 2023). According to Berk (2021) predictive policing consists of forecasting where and when future crime is highly likely to occur and this prediction is often based on spatial and

Article DOI: https://doi.org/10.37284/eajit.7.1.2141

temporal patterns. The police, therefore, allocate resources for addressing or preventing crime based on the resultant predictions.

Modern approaches to predictive policing heavily rely on data analysis (Berk, 2021; Schuilenburg & Soudijn, 2023), even though basic predictive policing has long been practiced based on experience and simple mapping, which involved recording displayed on maps (Berk, 2021), and exploiting spatial and temporal correlations for prediction (Schuilenburg & Soudijn, 2023; Sunde, 2022). Methods such as model-based approaches (Galič et al., 2022; Shad, 2023), synopsis-based approaches (Schuilenburg & Soudijn, 2023; Shad, 2023), and algorithm-based approaches (Galič et al., 2022; Schuilenburg & Soudijn, 2023; Sunde, 2022) have been used for predictive policing.

On one hand, method-based approaches use theories or statistical models of crime generation to predict criminal occurrences (Berk, 2021; Galič et al., 2022); whereas synopsis-based methods rely on empirical summaries of crime data (Galič et al., 2022; Schuilenburg & Soudijn, 2023). On the other hand, algorithm-based approaches use artificial narrow intelligence techniques to predict criminal occurrences (Schuilenburg & Soudijn, 2023; Sunde, 2022). Berk, (2021) note that modern crime forecasting typically uses self-exciting point process models, which are essentially statistical models for counts in time and space. These models presume that criminal activities influence each other and incorporate spatial and temporal declines that are based on kernel-density procedures. However, Berk notes that the forecasting accuracy of this model is largely influenced by various factors and is also data-set dependent.

In the United States, Predpol has been adopted by several police departments across the country. The tool uses data on past crimes to predict future criminal activity in specific areas (Mugari & Obioha, 2021). Therefore, law enforcement officers leverage data-driven insights from the tool to allocate resources more effectively in the quest to prevent or address crime in the country (Meijer & Wessels, 2019; Mugari & Obioha, 2021). Predictive policing is also widely adopted across Europe in countries such as Germany, Netherlands, Austria, Estonia, France, and Romania (Shad, 2023; Söderholm, 2023; Sunde, 2022).

Besides, other European countries such as Luxembourg, Portugal, and Spain are also exploring the possibilities of incorporating predictive policing in their law enforcement framework (Shad, 2023; Söderholm, 2023; Sunde, 2022). Netherland has played a pioneering role in this regard, and had deployed predictive policing on a national scale targeting various crimes, which has targeted violent crimes, domestic burglary, pickpocketing, commercial burglaries, car theft, and bicycle theft. The Crime Anticipation System (CAS) in the Netherlands had taken into account the demographic and socioeconomic data from multiple sources and used it to generate heat maps that reflect the crime-prone zones that should be focused upon with specific interventions (Galič et al., 2022; Sunde, 2022).

Germany has developed the Precobs system that targets residential burglary using historical crime data drawn from the five past years (Söderholm, 2023). Austria and France have also used AI-based predictive policing to detect residential and vehicle burglary. In particular, Austria uses historical crime data, whereas France uses a broad scope of data including filed complaints, historical crime statistics, geolocations, and potentially meteorological and national statistics (Galič et al., 2022; Söderholm, 2023).

According to Singh (2022), South Africa is more invested in deploying the face recognition technology despite the cautious approach towards the use of the technology as evidenced by the 2021 vote by the European Parliament to ban its use by law enforcement agencies in public spaces. South Africa is deploying the technology through the collaboration between law enforcement and the national Department of Home Affairs. However, there are concerns regarding data sharing, alignment with existing legislation, and potential targeting of people of color.

Article DOI: https://doi.org/10.37284/eajit.7.1.2141

Risk Assessment and Decision Making

Criminologists have adopted AI use in assessing risks and making decisions regarding criminal cases (Berk, 2021; Dencik et al., 2019; Ezzeddine et al., 2023Spivak & Shepherd, 2021; Thao, 2023). Berk, (2021) differentiates risk assessment from predictive policing arguing that while the later forecasts crimes based on the place and time, the former forecast crime taking into account characteristics of particular individuals. Therefore, risk assessment is rather an actuarial process that focuses on identifying features strongly associated with criminal behavior (Mugari & Obioha, 2021) and is quite similar to forecasting other outcomes like health risks or job performance (Berk, 2021; Dencik et al., 2019).

Risk assessment has for long been used in the criminal justice system in the United States and has influenced the parole decisions since the 1920s, and had incorporated artificial narrow intelligence even before the advent of predictive policing (Dencik et al., 2019). In the US risk assessment is used to determine various criminal justice decisions such as sentencing, parole release, probation/parole supervision, release determinations, and prison security levels (Berk, 2021; Spivak & Shepherd, 2021).

According to Spivak & Shepherd (2021) there are similarities between the traditional risk assessment methods and AI-based ones, examples of which being the regression models. They, however, noted that AI provide a broad scope of algorithms, which include supervised learning and reinforcement learning that offer more predictive accuracy. Spivak & Shepherd, however, advocated for human oversight in automating processes such as predictive validation considering that purely automated systems are highly likely to overlook the dynamic factors that influence outcomes.

Criminologists in Vietnam have found AI to be an invaluable tool for aiding their risk assessment processes for particular crimes, which thus inform their decision making framework (Thao, 2023). However, Thao cautioned that criminologists need to use AI as an assistive or supporting tool rather than a replacement of their judgment as human experts as this will go a long way in avoiding the ethical concerns that are associated with the use of the technology. In the United States, the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) is broadly used to assess risk associated with recidivism among offenders (Meijer & Wessels, 2019; Mugari & Obioha, 2021). This tool analyzes factors such as criminal history of individuals with the aim of predicting their likelihood to reoffend (Meijer & Wessels, 2019). The tool, therefore, inform decisions regarding bailing, parole and sentencing (Mugari & Obioha, 2021).

In the United Kingdom (UK), the Harm Assessment Risk Tool (HART) has been deployed by the Durham Constabulary. This AI tool uses machine learning to predict the risk of individuals committing serious crimes (Dencik et al., 2019; Ezzeddine et al., 2023; Oswald et al., 2017). The tool assesses various data points, which may include the past criminal behavior of individuals and their socio-demographic information (Sachoulidou, 2023). Besides, UK has established the National Data Analytics Solution (NDAS), which is used to identify individuals at high risk of committing violent crimes (Dencik et al., 2019; Ezzeddine et al., 2023). The tool was developed by the West Midlands Police and is effective when it comes to integrating data from various sources to provide law enforcement agencies with actionable intelligence for preventing crime (Sachoulidou, 2023; Oswald et al., 2017).

Besides, China uses the Integrated Joint Operations Platform (IJOP) in Xinjiang to aggregate data from various sources, including CCTV footage, internet usage, and financial transactions (Clarke, 2021). The tool uses these data to assess potential risks and identify suspicious behavior. The tool is considered effective for helping China to enhance surveillance and maintain public security (Caine, 2021; Clarke, 2021). In Netherlands, the Crime Anticipation System (CAS) has been deployed in

Article DOI: https://doi.org/10.37284/eajit.7.1.2141

Amsterdam and other cities and is used to predict where and when crime is highly likely to occur (Drenth & Van Steden, 2021; Strikwerda, 2021; Van Steden et al., 2013). The police, therefore, use the CAS to analyze historical crime data and other variables, such as weather and events and employ the resulting insight in the allocation of resources and for strategic planning (Drenth & Van Steden, 2021).

The use of AI in crime management has also been adopted in African countries. For instance, South Africa has deployed ShotSpotter in Cape Town. This AI-driven gun-shot detection system uses acoustic sensors to identify and locate gunfire incidents in real-time. Law enforcement agencies, therefore, analyze this data in real time and respond faster and accurately to shooting incidents (Swart, 2023). South Africa has also deployed Smart Policing Initiative in Johannesburg, which integrates AI and data analytics (Singh, 2022). The system uses surveillance cameras in the city, which are equipped with AI to monitor and predict criminal activities in real-time. This enables law enforcement officers to respond to crime incidents more quickly and also allocate resources based on crime hotspots (Seseni et al., 2023; Singh, 2022).

In Rwanda, the Safe City Project uses advanced surveillance systems integrated with AI. The system is strategically installed around public places in Kigali, and monitors or detects unusual activities such as traffic violations, suspicious movements, or unauthorized gatherings (Baffoe et al., 2020; Mutesi & Abbott, 2013). When law enforcement agencies detect such anomalies using these AI tools they send alert for quick response. The Safe City Project is reflective of the commitment by Rwanda to harness technology for public safety and has set a benchmark for other African countries (Baffoe et al., 2020).

In Kenya, law enforcement agencies have adopted crime mapping and predictive policing to enhance their capabilities for managing crime in the country (Lucho, 2023). The AI systems analyze extensive datasets such as historical crime records, socio-economic data, and environmental factors to identify patterns and crime hotspots (Baraka & Murimi, 2021; Baraka, 2023, Lucho, 2023). In particular, Nairobi County Government has partnered with tech companies to implement data analytics solutions that integrate with existing surveillance infrastructure (Baraka & Murimi, 2019; Gachemi, 2018, Lucho, 2023). The tool has helped in real-time monitoring and to also anticipate potential criminal activities (Baraka & Murimi, 2021; Baraka, 2023). The use of these tools have been aimed at reducing crime rates, improving response times, and optimizing patrol routes, contributing to a safer urban environment (Baraka & Murimi, 2019; Gachemi, 2018).

The literature on the use of AI models for risk assessment on criminal matters in Africa are largely lacking. However, governments have fast acknowledged the role that technology could play in the management of crime. While associated development plans and policies have been established in response to this need, particularly in countries such as Kenya, the actual implementation of the same is still pending. These delays could be attributed to the high costs involved in installing required technologies and training the personnel who will be charged with operationalizing the techy tools.

The reviewed literature, therefore, acknowledge that criminologists leverage AI tools to assess risks and make decisions regarding criminal cases, thereby using individual characteristics to forecast crime rather than rely on rather than just spatial and temporal patterns alone. Examples of these include COMPAS system in the US, which aids in determining parole and sentencing decisions; the Harm Assessment Risk Tool (HART) and the National Data Analytics Solution (NDAS) in the UK, which is used to predict serious crime risks and integrate diverse data sources for actionable intelligence; the Integrated Joint Operations Platform (IJOP) in Xinjiang, China, which is used for various surveillance purposes. However, while the AI models are effective in their risk assessment tasks, there is need for criminologists to inject human oversight

Article DOI: https://doi.org/10.37284/eajit.7.1.2141

into their operationalization to ensure their accuracy and ethical application.

Victim Identification and Assistance

The use of AI in victim identification and assistance has resulted in transformative changes in victim identification and assistance (Awe et al., 2023; Dakalbab et al., 2022; Piraianu et al., 2023). The use of facial recognition and biometric analysis, for instance, has been credited to efficiency and accuracy in the identification of victims (Awe et al., 2023; Piraianu et al., 2023). Dakalbab et al. (2022) note that AI analyses vast datasets and cross-referencing multiple sources such as social media, surveillance footage, and official records to match the characteristics of victims with the available information. This reduces the time that is required to identify victims as compared to the traditional methods.

Dakalbab et al. (2022) further note that AI is also used to inform victim assistance. The natural language processing algorithm analyzes communication patterns to detect distress signals in online interactions. Law enforcement authorities use this insight to identify potential victims of abuse or exploitation. Piraianu et al. (2023) observe that AI-powered chatbots and virtual assistants provide information on legal rights, safety planning, and emotional support resources. This provide immediate support to the victims by ensuring that they can access help around the clock (Dakalbab et al., 2022; Piraianu et al., 2023).

The use of AI in identifying victims and coordinating their assistance has been adopted in various countries across the globe. In Germany, for instance, AI has been used for victim support and provide assistance to asylum seekers and refugees. The German Red Cross uses AI chatbots to provide legal advice, counseling, and integration support to refugees and help them navigate the complexities of the asylum process and access essential services (Ediae et al., 2024; Shrivastava, 2023). In United Kingdom, AI-driven systems assist to identify victims of crime and provide support (Fontes et al., 2022; Peter 2022). For instance, the Metropolitan Police Service has deployed facial recognition technology in public spaces to identify missing persons and individuals involved in criminal activities (Peter 2022; Urquhart & Miranda, Murray, 2023; Urquhart & Miranda, 2022). The agency also uses AI to analyze data from various sources to track and assist victims of domestic abuse. This ensures timely intervention and support (Fontes et al., 2022; Urquhart & Miranda, 2022).

In the United States, the Thorn and the National Center for Missing & Exploited Children (NCMEC) uses AI to analyze online adverts and social media for indicators of human trafficking (L'Hoiry et al., 2024; Minnaar, 2024). Through AI tool, the agency effectively human trafficking victims and connect them with necessary services (Van der Watt, 2023). India has established Traffik Analysis Hub, which deploys AI tools in the mapping and predicting of human trafficking and child exploitation routes. The analyses help law enforcement authorities in corresponding prevention and victim support (Stockhem, 2020).

The Australian Federal Police also use AI analyze social media and communication platforms with the objective of detecting detect signs of abuse and exploitation for victims of domestic violence and child abuse (Singh & Nambiar, 2024; Subramani et al., 2018). In this way the police identify high-risk individuals and communities and can target intervention and prevention efforts (Novitzky et al., 2023). In South Africa, the Missing Children South Africa identifies and locates missing children using AI to analyze social media and online platforms (Pasha et al., 2022). Besides, the police in South Africa use AI-driven facial recognition systems to identify crime victims and perpetrators in public spaces (Emser & Van der Watt, 2019).

Notably, victim identification is a very important function for criminologists to undertake considering that for the most part, criminology has focused on the rights, interests and welfare of the accused person and relegated the victims of crime to the periphery. Therefore, the adoption of AI

Article DOI: https://doi.org/10.37284/eajit.7.1.2141

models in identifying victims is a significant corrective approach that should be encouraged across board. As evidenced by the reviewed literature AI models have provided capabilities that have transformed victim identification and therefore, streamlined their access to subsequent support. The use of AI models such as facial recognition, biometric analysis, and natural language processing have fastened up the process of identifying victims and therefore, availing support that they need to mitigate negative consequences of their victimization. For instance, victims can access legal, safety, and emotional support around the clock through AI-powered chatbots and virtual assistants. For instance, AI chatbots assist refugee in Germany, and also AI helps the Metropolitan Police identify and support domestic abuse victims in the UK.

A salient feature that make the adoption of these technologies timely is that they enable rapid and accurate identification of victims and this is increasingly important particularly when in cases such as human trafficking or domestic abuse, where law enforcement officers need to respond as fast as possible. With the use of facial recognition and biometric analysis, for instance, it becomes easier for law enforcement officers to quickly match physical characteristics of individuals. They are also able to analyze the communication patterns between individuals and detect distress signals in text-based interactions, and therefore, act accordingly. However, like all the other AI models that are used by criminologists, there is need for those using them to ensure that they protect the privacy of individuals and also avoid potential biases. They need to handle the data with utmost care so that they can adequately safeguard the rights and dignity of victims of crime. Without such human intervention the use of the AI tools does not guarantee that the victims will be identified and helped out in time as they are intended to function.

Enhance Correctional Facility Services

According to Dakalbab et al. (2022) the use of AI in correctional institutions across the globe is fast becoming a transformational force, particularly with regard to improving their operational efficiency, safety, and rehabilitation outcomes. Emser & Van der Watt, (2019) concur with this observation and further points out that there are various domains within correctional systems where AI models can be used, which include security, inmate management, and rehabilitation programs. Different countries are deploying AI models in their correctional institutions in varying degree of sophistication and success in response to the global trends that demand a shift toward smarter, more efficient correctional facilities (Emser & Van der Watt, 2019; L'Hoiry et al., 2024).

In the US, AI models have proved effective in enhancing security and operational efficiency within prisons. In particular, correctional facilities use facial recognition and behavioral analysis to monitor their inmates and predict any possible potential security threats that they may pose to themselves, or others (Berk, 2021; Spivak & Shepherd, 2021). The authorities use these systems to identify unusual patterns of movement or behavior and then alert relevant personnel on possible disturbances before they escalate (Spivak & Shepherd, 2021). The predictive capacity of these AI tool not only improve safety; they also inform more efficient allocation of resources since they can now deploy their staff more strategically based on real-time data (Dencik et al., 2019; Spivak & Shepherd, 2021).

In Europe, the United Kingdom has explored the use of AI models to improve inmate rehabilitation and reduce recidivism. Consequently, AI-based educational programs and mental health support systems have been developed and tested to ascertain their potential for providing personalized learning and therapy sessions (Dencik et al., 2019; Ezzeddine et al., 2023; Oswald et al., 2017). The systems rely on AI to adapt content based on progress and needs individual inmates and ensure that they receive the most effective support (Ezzeddine et al., 2023). Besides, the predictive capabilities of the models assess the risk of reoffending and, thus enable the parole boards make more informed decisions.

Article DOI: https://doi.org/10.37284/eajit.7.1.2141

Consequently, the boards are at a better place to tailor their post-release support services accordingly (Dencik et al., 2019; Ezzeddine et al., 2023).

Australia uses AI in their correctional facilities to enhance their security and rehabilitation. They have achieved this by developing AI-based risk assessment tools, which prison authorities use to evaluate the likelihood of inmates to engage in in violent behavior or attempt to escape (Novitzky et al., 2023). The authorities use the resulting analyses to make better management decisions and to establish more effective preventative measures (Singh & Nambiar, 2024; Subramani et al., 2018). Apart from that, Australian correctional facilities seek to improve the employability of the inmates upon release by leveraging AI for vocational training programs that align with market demands (Novitzky et al., 2023); which is necessary for reducing the recidivism rates in the country and particularly amongst the youth for minority groups (Novitzky et al., 2023; Subramani et al., 2018).

The use of AI in the criminal justice system in South Africa has indeed extended to the correctional institutions, making it one of the most technologically advanced countries on the continent (Seseni et al., 2023; Singh, 2022). The Department of Correctional Services has explored technological solutions for addressing various challenges experienced in the correctional facilities in the country (Emser & Van der Watt, 2019; Singh, 2022). One of these significant challenges include overcrowding and the Department has initiated specific large-scale AI projects that are yet to be rolled country-wide, which are implemented in collaboration with tech companies and are aimed at improving the existing rehabilitation programs (Emser & Van der Watt, 2019; Seseni et al., 2023; Swart, 2023).

The Nigerian Correctional Service is also working towards modernizing their correctional facilities by integrating digital tools and AI to improve their management and operational efficiency. They have so far deployed AI for monitoring and data analysis to better understand inmate behavior and needs with the aim of establishing more targeted rehabilitation programs (Emser & Van der Watt, 2019).

Extant literature, therefore, demonstrate the invaluable role of data and algorithms in informing predictive policing, which criminologists are using to anticipate activities carried out by criminals. This is imperative considering the fact that criminals are also using technology as a tool for advancing their nefarious objectives. It is, therefore, imperative for criminologists to also use technology to preempt criminal activities whether conducted online or offline. In this regard, the modern approaches including model-based, synopsis-based, and algorithm-based methods are instructive in forecasting crime based on spatial and temporal trends. As evident with the case of Predpol in the US and the Crime Anticipation System (CAS) in the Netherlands, AI models have proved invaluable when it comes to helping criminologists, particularly law enforcement agencies to better understand crime through the crime maps that the models generate. The same case applies in European countries such as Germany with its Precobs system and Austria and France where AI models help law enforcement agencies to detect crime including residential and vehicle burglaries. Worth noting, however, is the fact that the use of these predictive AI models come with potential biases and data privacy issues that criminologists must not ignore.

While the use of AI in correctional facilities across the globe reflects the fact that diverse applications of AI are currently deployed to improve on the operational efficiency, safety, and rehabilitation outcomes of these facilities, there is a need for a critical analysis to be conducted to appreciate their implications and potential challenges. A key outcome of the use of these AI tools in the correctional context is the optimization of resource allocation, which is based on real-time data and is expected to translate into more effective management of correctional facilities. There are also attendant ethical considerations that play at the background

Article DOI: https://doi.org/10.37284/eajit.7.1.2141

in the use of these tools as evident with privacy issues and the potential for misuse of data. There is also the fear that continuous monitoring creates a pervasive sense of being watched, which can lead to mental health issues amongst the inmates.

If the biases associated with the use of AI, which could be overcome by retraining the models with objective data then the resultant tools have the potential of assessing recidivism risks and informing parole decisions in a more effective manner through the data-driven approach. This is a critical departure from the traditional parole mechanisms where subjectivism was hard to address due to the manual nature of the process. However, criminologists must also beware of overlying on these models. They need to ensure that human judgment and oversight remain central to the processes that contribute towards decision-making; this is the only way they can effectively account for nuances that algorithms might miss.

In sum, criminologists have significantly integrated technology in their work and particularly the use of AI models. This reflects the general trends in the socioeconomic developments across the globe where technology has permeated every sphere. Criminologists have, in turn, deployed these AI models as tool for enhancing various aspects of their roles including advancing law enforcement, judicial decision-making, victim support, and correctional management. The use of these AI models calls into question the ethical and privacy implications that they portend, which criminologists have to take into account.

SOCIAL IMPACT OF THE USE OF AI IN CRIMINOLOGY

There are both positive and negative social effects of the use of AI in criminology. The positive aspects of AI use in criminology have been elaborated above as including predictive policing; crime risk assessment and decision making; and victim identification and assistance. In the same vein, the adoption of technology and particularly AI in criminology has presented significant social implications that criminologists have had to grapple with. These include bias and discrimination; privacy concerns; opaque AI decision-making processes; and effects on employment opportunities.

Bias and Discrimination

According to Malek (2022), when it comes to the use of AI systems in criminology, bias and discrimination are informed by the fact that the systems are trained by subjective data, which ends up generating the algorithm that processes the data. For instance, the training of AI tools with historical data ends up invariably reflecting the existent social biases. This is evident considering that in almost all societies there are some particular communities that have been over-policed as compared to others (Begishev et al., 2023; Malek, 2022). Therefore, AI models that are trained on these data disproportionately predict crime in those areas or communities and end up perpetuating a cycle of bias and discrimination (Begishev et al., 2023).

The bias and discrimination associated with the AI models used in criminology are attributed to predictors such as historical data (Alvarez et al., 2024; Malek, 2022); algorithmic bias (Spivak & Shepherd, 2021); and feedback loops (Alvarez et al., 2024; Malek, 2022). Historical data reflects the systemic and historical inequalities that exist in society characterized by racial profiling whereby some particular minority communities have been subjected to more intensive policing and surveillance as compared to others (Begishev et al., 2023).

This intensive police scrutiny to these communities has resulted in increased recorded crime in the communities and this data is used to train AI models, which eventually associate these communities with higher crime rates and end up perpetuating a cycle of over-policing (Alvarez et al., 2024; Malek, 2022; Spivak & Shepherd, 2021). Therefore, the use of AI models to predict crime result in the reinforcement of these existing prejudices and stereotypes (Alvarez et al., 2024). Consequently, based on these predictions law enforcement agencies have been inclined to target more police resources amongst minority

Article DOI: https://doi.org/10.37284/eajit.7.1.2141

neighborhoods, which leads to increased arrests and collection of more data that further entrench the bias (Begishev et al., 2023; Spivak & Shepherd, 2021).

Shad (2023) noted that AI algorithms oversimplify complex social phenomena, which often translate into unjustifiable disadvantage and discrimination that in most cases negatively affect minority groups residing in high-crime areas. Shad faulted AI-based predictive policing for engendering normative disorder that is characterized by false ‘second natures’, thereby masquerading as natural laws, which exert significant influence over individuals. The difference between these false norms and the conventional social norm is they deprive individuals of the agency to choose whether to adhere to them and this results in their pervasive impact on the ethical fabric of the society. The study concluded that as the false social norms get more entrenched, individuals assimilate them into their worldview and this results in a change in their thoughts, feelings, and actions. The resultant transformation is characterized by a profound shift in societal norms.

In most instances, the predictive and preventive power of AI use in criminology has resulted into an increase in resource allocation to areas that are identified by analytics as being crime zones. This automatic and rather, merited response has been characterized by the increase in policing to serve both as a deterrent and also ensure immediate response to criminal occurrences (Begishev et al., 2023; Spivak & Shepherd, 2021). Notably, increased police presence amongst minority community intensify resentment to the authorities. In the first place, the police operating in these communities come with predetermined mindsets that compromise their professionalism in the exercising of their roles and responsibilities. Due to this, they end up victimizing members of the communities by suspecting them for crimes that they may not have committed and, thus subjecting them to the criminal justice processes unfairly. It is also important to note that because of the preconceived notions about the minority communities, those who are thus arrested and arraigned unfairly are easily convicted, largely because they may also lack the means to access legal defense services. The concentration of police presence and resources in the minority communities also present unintended consequences in the sense that those communities that are deemed to be more secure than they actually are end up being denied resources that they need to manage or rather prevent crime. These ‘safe’ communities also experience underreporting of criminal activities since the law enforcement agencies have focused their time and resources elsewhere.

Halley (2022) faults the logic and bias that is inherent in such predictive policing approaches arguing that increased police presence within a particular neighborhood, for instance, does not necessarily reflect increased crime rates. Halley (2022) further note that such as feedback loop has ended up perpetuating policing practices, which are blamed for causing inaccurate allocation of resources and entrenching negative stereotypes about certain communities. This is particularly the case where machine learning algorithms are trained using biased data and the resultant AI tool, therefore, ends up replicating and exacerbating the biases and advancing the skewed perceptions of crime risk.

Begishev et al., (2023) concur that there are inherent inaccuracies and biases that come with the use of automated policing technologies and more particularly the facial recognition system. These systems are accused of misidentifying individuals and entrenching discrimination, which often affects people of color disproportionately, leading to human rights violations or wrongful arrests. Halley (2022) further notes that such violations are present in cases where AI tools are used without human oversight. This, in itself, presents an accountability gap, which makes it increasingly difficult to clarify the responsibility for errors.

Bias and discrimination is also a function of socio-economic disparities within a particular society. Extant literature, for instance, has associated high incidents of criminal activities with higher poverty rates (Begishev et al., 2023). In many instances, many official records have also indicated similar trends with regard the intersection between crime and socio-economic predictors. This data has been used to train AI models and may incorrectly equate poverty with higher criminal propensity; thereby, translating into biased predictions that unfairly target low-income neighborhoods (Alvarez et al., 2024; Malek, 2022). According to Spivak & Shepherd, (2021) this is one of the major causes of discriminatory practices within the justice system. For example, AI based risk assessment tools that are used to predict the likelihood of reoffending may unfairly classify individuals from minority backgrounds as high-risk and therefore, influence the decisions regarding parole, bail and sentencing.

Additionally, unequal law enforcement practices have also contributed to the bias and discrimination that is associated with AI models used in criminology. In most cases, historical data reflects biases in law enforcement practices, which is evidenced by the differential treatment based on race, gender, or ethnicity (Malek, 2022; Spivak & Shepherd, 2021). For example, drug-related arrests are frequent amongst minority communities even though there are similar usage rates across different groups. When this data is embedded in the training of AI models it ends up informing their skewed predictions (Begishev et al., 2023).

Spivak & Shepherd (2021) noted that there are biases that are inherent in the outcome criteria used for evaluation when using AI-based risk assessment, irrespective of the method that may be selected for use. They noted the difficulty of trying to achieve total equality in risk assessment and, therefore, called for measures to reduce racial disparities, which they observed that AI presented significant potential in that regard. Furthermore, they noted that transparency is a major concern when it comes to using AI for crime risk assessment due to the opacity of both AI algorithms and human judgment. Undoubtedly, AI offers more explicit insights into decision-making processes; the technology, however, raises questions about informed consent and understanding the basis of assessments.

Outside liberal democracy contexts, the use of AI tools in law enforcement provide authoritarian regimes with perfect tools for entrenching oppression of its citizenry. According to Halley (2022) the potential for law enforcement agencies to use automated policing technologies to infringe on the rights and freedoms of citizens in undemocratic states are abundant. This is evident considering the heightened level of surveillance in such political contexts where the ruling elite are wary of dissenting voices and live in constant fear of being hounded out of power. In China, for instance, the deployment of facial recognition technology has been associated with government overreach, which has been characterized with infringement of individual freedoms and liberties.

Privacy Concerns

Privacy issues regarding the use of AI in criminology is a significant concern that is multifaceted as well. According to Farayola et al., (2023) these issues are occasioned by the extensive data collection, analyses and data storage practices that these AI models require to function optimally. Notably, the AI models heavily depend on a vast amount to data to establish patterns and make their predictions. In most cases, these data consist of criminal records, social media activity, financial transactions, and location data of particular individuals or communities (Farayola et al., 2023; Rodrigues, 2020). The collection of such sensitive and detailed data has brought into question the level to which the privacy of individuals has been compromised. Undoubtedly, citizens may fear that they are being monitored for every movement that they make or that they are being constantly surveilled (Spivak & Shepherd, 2021).

In 2021, the European Parliament voted against the use of Facial Recognition Technology by law enforcement agencies in public places (Alvarez et al., 2024), a development that underscored a

Article DOI: https://doi.org/10.37284/eajit.7.1.2141

pivotal moment in the global discourse on privacy, human rights, and technological surveillance (Begishev et al., 2023). The key motivation for this vote was to prevent potential infringement on individual privacy rights. The use of the technology in public spaces raised significant concerns regarding the erosion of personal privacy and the right to anonymity in public settings (Alvarez et al., 2024; Begishev et al., 2023).

This development signified that while AI technology may be helpful in helping combat and prevent criminality; its use must not trump the right and freedoms of individuals who are supposed to be protected by law enforcement agencies in the first place. Subramani et al., (2018) further argues that in spite of the purported advantaged that come with the use of AI tools in criminology, there are significant accuracy and fairness, particularly associated with face recognition algorithms, which tend to be biased against marginalized groups.

Begishev et al., (2023) note that the storage of large volumes of personal dataset invariably pose significant security risks. This is especially evident considering that data has become a commodity in this digital dispensation and cybercriminals are coming up with ways of accessing it for the purpose of commercializing it at the expense of their owners (Farayola et al., 2023). Due to this, law enforcement agencies are compelled to develop robust security measures to protect this data, which does not necessarily guarantee data security considering that even the best systems are still susceptible to cyberattacks (Spivak & Shepherd, 2021). Unauthorized access to such data by cybercriminals often translates into severe consequences to the privacy and safety of individuals (Begishev et al., 2023; Rodrigues, 2020).

Spivak & Shepherd (2021) caution of the possibility of misuse for data that is collected for the criminological purposes. The data, for instance, could be used beyond its intended scope to target or rather profile individuals based on characteristics like race or socio-economic status. Farayola et al., (2023) concurs that such misuse has contributed to discriminatory practices and the unfair targeting of specific groups, particularly minority groups, and this eventually undermine the trust the public has in law enforcement and the justice system.

The breach of privacy of individuals resulting from the use of AI models in criminology is closely related to the erosion of civil liberties. Freedom of expression is stifled when individuals become aware that they are being watched or monitored (Farayola et al., 2023), and this undermines the principle of a free society. Furthermore, the balance between privacy and security is a key concern in the context of AI use in criminology (Authors et al., 2024; Farayola et al., 2023).

The privacy issues that are presented by the use of AI have been contested or debated in various countries across the globe. In Australia where AI models have been used to aid in criminal investigations, but they have at the same time presented significant concerns, particularly with large language models (LLMs) (Broadhurst, et al., 2019; Manheim & Kaplan, 2019). These models rely on vast amounts of personal data including detailed personal histories and interactions with the legal system, which are very personal and sensitive. Notably, the models could be exploited to generate sophisticated phishing emails, malware, and other malicious content (Broadhurst, et al., 2019). Besides, it is also feared that cybercriminals could use LLMs undermine the integrity of the criminal justice system by manipulating legal data, fabricating evidence, or impersonate legal authorities (Broadhurst, et al., 2019; Harris & Burke, 2021).

Manheim & Kaplan, (2019) further note that the transparency and traceability of user interactions with LLMs is a major concern considering that in most cases it is not clear whether user inputs can be traced back to them and how this data is stored or used. Confidentiality is crucial in criminology and, therefore, the possibility that LLMs may retain and expose user data poses a serious threat (Manheim & Kaplan, 2019). This demands of the

Article DOI: https://doi.org/10.37284/eajit.7.1.2141

law enforcement agencies using these models to ensure that they do not inadvertently compromise their own security or that for the suspect or victim that they are handling (Broadhurst, et al., 2019; Harris & Burke, 2021).

Opaque AI Decision-Making Processes

According to Putera et al., (2022) the transparency paradox associated with the use of AI in judicial decision-making has unparalleled effects to the rule of law in general. They noted that one of the constructs of the rule of law is its emphasis on the reciprocity between the government and the people, which therefore, requires that government enacts laws that are transparent and accessible to ensure predictability and accountability. The introduction of AI in criminology has raised concerns regarding maintaining this particular balance considering that AI models that use machine learning could be opaque or 'black-box' in nature. This in turn, makes the decision-making processes of these model quite complex and therefore, difficult to understand and scrutinize.

This lack of transparency associated with the use of AI undermines the authority of law enforcement agencies and the rule of law. Putera et al., (2022) argued that AI models should be transparent and thus, easy to interpret and explain. This was the key motivation for the European Commission for the Efficiency of Justice advocating for the use of AI that is premised on upholding the principles of non-discrimination, transparency, and respect for fundamental rights. However, the use of AI models such as COMPAS in the US have demonstrated the complexity of AI algorithms in the assessment of recidivism risk, thereby, posing significant challenges. In most cases, the AI tools do not how they arrive at decisions, which result in the lack of understanding and trust amongst those who have to bear the consequences of AI-driven decisions.

Effects on Employment Opportunities

Generally, there is increased concern about the lack of accountability and oversight in the use of AI technologies. For instance, government law enforcement agencies have often adopted the AI tools without establishing comprehensive safeguard for their use (Begishev et al., 2023; Singh & Nambiar, 2024); or providing their staff with adequate training on how to deploy them effectively and ethically (Halley, 2022). By default, rather than design, government have appeared to prioritize cost savings over constitutional rights and liberties (Novitzky et al., 2023). This shifts the responsibility to the tech firms who vend this particular tools to assume responsibility for the misuse of their products, even though there are no clear cut legal frameworks that have so far been put in place to hold them accountable (Begishev et al., 2023; Singh & Nambiar, 2024).

Therefore, as revealed in this review the use of AI models in criminology present significant benefits one hand and also critical social implications on the other hand. The social implications include bias, privacy invasion, lack of transparency, and employment disruption, which need to be adequately managed to ensure effective application of the AI models. There is a need for investigating or rather examining the historical data that is used to train AI models for the purpose of working out the social biases that keep replicating and amplifying, and leading to disproportionate predictions.

INTERVENTIONS FOR NEGATIVE SOCIAL IMPACT OF AI USE

Various interventions could be adopted to counteract the negative social impact of using AI in criminology. These include strengthening the regulatory framework; ensure the injection of human oversight in the use of the tools; transparency and accountability; and enhance collaboration between the key stakeholders using AI in criminology.

Regulatory Framework

The establishment of a robust regulatory framework is considered essential for ensuring that the expediting of criminal processes and proceedings using AI does not compromise individual rights and the fairness of criminal proceedings (Begishev et al., 2023; Halley, 2022;

Article DOI: https://doi.org/10.37284/eajit.7.1.2141

Thao, 2023; Spivak & Shepherd, 2021; Singh & Nambiar, 2024). Thao (2023) suggested the prioritization of the development of a robust regulatory framework and remedial mechanisms for mitigating attendant ethical risks associated with the use of AI in criminology. Thao argued that the successful integration of AI is closely correlated with striking a between technological innovation and safeguarding fundamental human rights.

Halley (2022) noted that law enforcement agencies, such as the Toronto Police Services Board have taken adequate measures to strengthen the regulation of AI use in addressing crime. However, there is also need for broader action to address the systemic issues surrounding the use of automated policing, which include the suspension of predictive policing programs that advance discriminatory practices in the criminal justice system. As L'Hoiry et al., (2024) contends, issues such as algorithmic bias, misidentification, and disproportionate surveillance underscore the need for establishing robust regulation and oversight.

Broadhurst, et al., (2019) concur that the lack of robust regulatory frameworks exacerbates the risks that are associated with these privacy issues. In many countries, including Australia, the existing legal and regulatory frameworks have not been established in a way that they can comprehensively address the challenges that the use of AI present, and particularly with regard to criminology (Manheim & Kaplan, 2019; Singh & Nambiar, 2024). In the case, of Australia, these regulatory gaps imply that the use of LLMs in criminology functions within a legal gray area, which increases the possibilities of privacy breaches without having adequate legal recourse or protection (Singh & Nambiar, 2024).

Human Oversight

According to Novitzky et al., (2023) human oversight is essential for mitigating AI-driven security threats that often emanate from outdated or incomplete data that can distort AI outcomes. This has been blamed for missed anomalies and biased AI models, which often undermine the efforts that law enforcement agencies put in place to curb or prevent crime in society (Ediae et al., 2024). Therefore, law enforcement officers in charge of cybersecurity need to continuously monitor and update AI models with new insights (L'Hoiry et al., 2024).

The law enforcement agencies also need to conducted regular audits and data assessments to identify and rectify biases and also ensure that the data used to train the models reflect a balanced representation of the contextual realities (Emser & Van der Watt, 2019). This is necessary for ensuring that the data biases that can cause false positives; the misguiding inaccurate data and the incomplete data that can obscure security risks are addressed adequately before they distort the understanding of particular crime situations (Spivak & Shepherd, 2021).

Extant literature has underscored the role of human oversight in ensuring the efficacy of the use of AI technologies in crime detection, prediction and prevention (L'Hoiry et al., 2024; Novitzky et al., 2023; Singh & Nambiar, 2024). For instance, Spivak & Shepherd (2021) reiterated the significance of human judgment and oversight in the deployment of automated processes such as predictive validation, which they considered necessary in ensuring that decisions are not solely reliant on algorithms but also take into account the dynamic factors that influence outcomes.

Continuous evaluation of the efficacy of the AI tools being used is also necessary for ensuring that necessary improvements are made to address any ethical concerns that emerge with the use of the tools (Ediae et al., 2024; Singh & Nambiar, 2024). According to Spivak & Shepherd (2021) ongoing evaluation and refinement of AI-based risk assessment models is required to assess the predictive performance of the tools using new data, and to also understand impact of interventions based on assessment results.

Transparency and Accountability

Putera et al., (2022) recommended the training of AI models in such a way that they become capable of providing the rationale for their decisions. This

Article DOI: https://doi.org/10.37284/eajit.7.1.2141

is imperative for ensuring that their use in criminology is associated with transparency and accountability. In this way, it will become possible for criminologist who are using the models to detect any emerging errors or arbitrary actions and, thereafter, support challenges against decisions. Putera et al., further argue that it is imperative for criminologists to understand the AI tools that they are using as this puts them in a position where they can intervene to make any corrections from the output of the tools, and influence credible decision making. Therefore, while the use of AI models in criminology is beneficial in various ways it must be approached with caution so that the core principles of the rule of law can be safeguarded.

Collaboration

According to Subramani et al., (2018) AI has played an integral role when it comes to enhancing cyber security and curbing other forms of criminal activities. However, for its potential to be harnessed there is a need for stakeholders to collaborate. This is particularly essential considering that attackers keep looking for ways to bypass AI-based security measures even as the technology and defense improve day by day (L'Hoiry et al., 2024). Therefore, collaborations amongst government agencies, vendors and partners is a significant proactive measure against evolving AI-driven cyber threats (Emser & Van der Watt, 2019; Spivak & Shepherd, 2021).

Novitzky et al., (2023) recommend disclosure and information sharing, considering them as pertinent in these collaborations in terms of helping stakeholders to understand the broader threat landscape and improve their own defenses. Emser & Van der Watt, (2019) further suggest engaging ethical hackers through bug bounty programs and live hacking events as an important facet of collaboration that provide insights about the cybercriminal tactics could be evaded, especially for those using AI models. Additionally, these collaborations play an integral role in enlightening the law enforcement officers about the stereotypes that they need to look out for when using the AI tools and how to avoid perpetuating them (Ediae et al., 2024; L'Hoiry et al., 2024; Singh & Nambiar, 2024). The collaboration can, therefore, serve as a peer review forum through which responsible use of AI tool is encouraged through collaboration (Singh & Nambiar, 2024).

CONCLUSION

This paper has used recent extant literature to examine the intersection between criminology and social impact with respect to the use of AI. The paper acknowledged that the advancement of technology and the proliferation of its use in various facets of life has invariably included the field of criminology. The adoption of technology by criminologists is even much more urgent considering that criminals have also leveraged tech tools in conducting their activities. It is therefore, imperative for criminologists to lead the way in the use of these tools, and more particularly AI models in the management and prevention of criminal activity in society. This paper, therefore, explored three distinct areas with regard to AI use in criminology including the use of the AI models, their negative social impact and requisite interventions that should be adopted to redress the negative consequences.

AI models have been used to enhance predictive policing; and crime risk assessment and decision making, which are pertinent in curbing crime and responding to it as soon as it occurs. The models have also played an integral role in victim identification and assistance, thereby ensuring the criminal justice system also takes into account the welfare of the victims in a timely manner. Additionally, the tools have supported effective decision-making and interventions in correctional facilities. However, the use of these models present significant challenges that criminologists need to take into account. These challenges are characterized by the bias and discrimination that are informed by the AI model outputs. These biased output are attributed to the stereotypical inputs that is used to train the model, which translate into slated output. The other challenges include the possibility of infringing upon the

Article DOI: https://doi.org/10.37284/eajit.7.1.2141

privacy concerns of people who may be surveilled by devices installed in the public.

Besides, the operations of most of these AI models are opaque and this becomes increasingly difficult to explain contested outputs, a factor that contribute to the distrust that is at times associated with the models. Additionally, the misleading outputs of the models have complicated chances for persons whose suitability for particular employment opportunities have been associated with analyses by the AI models.

In consideration of these challenges, this discourse outlined four key interventions that criminologists need to adopt to prevent the above mentioned challenges from undermining the effectiveness and efficiency of the AI models. This include the establishment of regulatory framework that guide how law enforcement agencies operationalize AI models. This will ensure that their use does not, for instance, involve breaches to individuals' rights to privacy. The discourse also recommended the integration of human oversight in the use of the AI models so that any inaccurate outputs can be corrected in time and any stereotypical perpetuation addressed accordingly.

Furthermore, transparency and accountability in the use of the tools also emerged as necessary for ensuring that the opaqueness of the models are addressed and that their use does not end up in the victimization of individuals. Besides, collaboration amongst stakeholders emerged as necessary for sharing information about the functioning of the tools, and undertaking modifications to make them more effective.

REFERENCES

Alvarez, J. M., Colmenarejo, A. B., Elobaid, A., Fabbrizzi, S., Fahimi, M., Ferrara, A., Ghodsi, S., Mougan, C., Papageorgiou, I., Reyero, P., Russo, M., Scott, K. M., State, L., Zhao, X., & Ruggieri, S. (2024). Policy advice and best practices on bias and fairness in AI. Ethics and Information Technology, 26(2), 31. https://doi.org/10.1007/s10676-024-09746-w

Authors, A., Luz, G., & Olaoye, G. (2024). Data quality and data privacy challenges in AI applications.

Awe, O., Pamilerin, O., & Omotosho, B. (2023). Importance of Artificial Intelligence as Evidence in Cases between Underage Victims of Rape and Offenders in Nigeria. African Journal of Social Sciences and Humanities Research, 6, 112– 123. https://doi.org/10.52589/AJSSHR-8HNKHLBB

Baffoe, G., Ahmad, S., & Bhandari, R. (2020). The road to sustainable Kigali: A contextualized analysis of the challenges. Cities, 105, 102838. https://doi.org/10.1016/j.cities.2020.102838

Baraka, G. E. (2023). An Evidence-based Theoretical Underpinning of Technological Transformation in Policing: From Manual Crime mapping to Geographic Information Systems in Kenya. https://doi.org/10.13140/RG.2.2.22835.91682

Baraka, G. E., & Murimi, S. (2019). Stuck in the past with push-pins on paper maps: Challenges of transition from manual to computerized crime mapping and analysis in Kenya. International Journal of Police Science & Management, 21, 36–47. https://doi.org/10.1177/1461355719832620

Baraka, G. E., & Murimi, S. K. (2021). Why geographic information systems in spatiotemporal crime analysis? Attitude of Kenyan police officers. Police Practice and Research, 22(5), 1453– 1468. https://doi.org/10.1080/15614263.2019.1689131

Begishev, I., Asli, M. R., Denisovich, V., Majorov, A., & Sergeyev, A. (2023). Research of artificial intelligence as a subject of crime. E3S Web of Conferences, 449, 03004. https://doi.org/10.1051/e3sconf/202344903004

Berk, R. A. (2021). Artificial Intelligence, Predictive Policing, and Risk Assessment for Law Enforcement. Annual Review of Criminology, 4(Volume 4, 2021), 209–237.

https://doi.org/10.1146/annurev-criminol-051520-012342

Broadhurst, R., Maxim, D., Brown, P., Trivedi, H., & Wang, J. (2019). Artificial Intelligence and Crime. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3407779

Cain, G. (2021). The Perfect Police State: An Undercover Odyssey into China's Terrifying Surveillance Dystopia of the Future. PublicAffairs.

Clarke, M. (2021). "No Cracks, no Blind Spots, no Gaps": Technologically-Enabled "Preventative" Counterterrorism and Mass Repression in Xinjiang, China. In A. Henschke, A. Reed, S. Robbins, & S. Miller (Eds.), Counter-Terrorism, Ethics and Technology: Emerging Challenges at the Frontiers of Counter-Terrorism (pp. 121–137). Springer International Publishing. https://doi.org/10.1007/978-3-030-90221-6_8

Dakalbab, F., Abu Talib, M., Abu Waraga, O., Bou Nassif, A., Abbas, S., & Nasir, Q. (2022). Artificial intelligence & crime prediction: A systematic literature review. Social Sciences & Humanities Open, 6(1), 100342. https://doi.org/10.1016/j.ssaho.2022.100342

Dencik, L., Redden, J., Hintz, A., & Warne, H. (2019). The 'golden view': Data-driven governance in the scoring society. Internet Policy Review, 8(2). https://policyreview.info/articles/analysis/golden-view-data-driven-governance-scoring-society

Drenth, A. R., & Van Steden, R. (2020). Everyday patrol work for a data-driven flying squad: Advancing theoretical thinking on police craftsmanship in interacting with civilians. Journal of Crime and Justice, 43(4), 486–501. https://doi.org/10.1080/0735648X.2020.1722202

Ediae, A., Chikwe, C., & Kuteesa, K. (2024). Leveraging Ai In Case Management For Vulnerable Migrants: A Path Toward Enhanced Resilience. Computer Science & IT Research Journal, 5, 985–1007. https://doi.org/10.51594/csitrj.v5i4.1084

Emser, M., & Van der Watt, M. (2019). #Stillnotfound: Missing Children in South Africa. Alternation: Interdisciplinary Journal for the Study of the Arts and Humanities in Southern Africa. https://doi.org/10.29086/2519-5476/2019/v26n1a5

Ezzeddine, Y., Bayerl, P. S., & Gibson, H. (2023). Safety, privacy, or both: Evaluating citizens' perspectives around artificial intelligence use by police forces. Policing and Society, 33(7), 861– 876. https://doi.org/10.1080/10439463.2023.2211813

Farayola, M. M., Tal, I., Connolly, R., Saber, T., & Bendechache, M. (2023). Ethics and Trustworthiness of AI for Predicting the Risk of Recidivism: A Systematic Literature Review. Information, 14(8), Article 8. https://doi.org/10.3390/info14080426

Fontes, C., Hohma, E., Corrigan, C. C., & Lütge, C. (2022). AI-powered public surveillance systems: Why we (might) need them and how we want them. Technology in Society, 71, 102137. https://doi.org/10.1016/j.techsoc.2022.102137

Gachemi, H. W. (2018). Development of a Crime Mapping Tool based on Social Media Data: A Case of Twitter in Nairobi, Mombasa and Kisumu. United States International University.

Galič, M., Das, A., & Schuilenburg, M. (2022). AI and administration of justice: Predictive policing and predictive justice in the Netherlands. https://doi.org/10.13140/RG.2.2.17944.88320

Halley, C. (2022). What Happens When Police Use AI to Predict and Prevent Crime? JSTOR Daily. https://daily.jstor.org/what- happens-when-police-use-ai-to-predict-and-prevent-crime/

Harris, H., & Burke, A. (2021). Artificial Intelligence, Policing and Ethics – a best practice model for AI enabled policing in Australia. 53– 58. https://doi.org/10.1109/EDOCW52865.2021.00032

Article DOI: https://doi.org/10.37284/eajit.7.1.2141

L'Hoiry, X., Moretti, A., & Antonopoulos, G. (2024). Human trafficking, sexual exploitation and digital technologies. Trends in Organized Crime, 27, 1–9. https://doi.org/10.1007/s12117-024-09526-4

Malek, Md. A. (2022). Criminal courts' artificial intelligence: The way it reinforces bias and discrimination. AI and Ethics, 2, 1–13. https://doi.org/10.1007/s43681-022-00137-9

Manheim, K., & Kaplan, L. (2019). Artificial Intelligence: Risks to Privacy and Democracy. The Yale Journal of Law and Technology, 21. https://yjolt.org/sites/default/files/21_yale_j.l._tech._106_0.pdf

Meijer, A., & Wessels, M. (2019). Predictive Policing: Review of Benefits and Drawbacks. International Journal of Public Administration, 42(12), 1031– 1039. https://doi.org/10.1080/01900692.2019.1575664

Minnaar, A. (2024). An examination of early international and national efforts to combat online child pornography and child sexual exploitation and abuse material on the Internet. Child Abuse Research, 24(2). https://doi.org/10.10520/ejc-carsa_v24_n2_a1

Mugari, I., & Obioha, E. E. (2021). Predictive Policing and Crime Control in The United States of America and Europe: Trends in a Decade of Research and the Future of Predictive Policing. Social Sciences, 10(6), Article 6. https://doi.org/10.3390/socsci10060234

Murray, D. (2023). Police Use of Retrospective Facial Recognition Technology: A Step Change in Surveillance Capability Necessitating an Evolution of the Human Rights Law Framework. The Modern Law Review, n/a(n/a). https://doi.org/10.1111/1468-2230.12862

Mutesi, L., & Abbott, P. (2013). Kigali Safe City for Women and Girls.

Novitzky, P., Janssen, J., & Kokkeler, B. (2023). A systematic review of ethical challenges and opportunities of addressing domestic violence with AI-technologies and online tools. Heliyon, 9(6), e17140. https://doi.org/10.1016/j.heliyon.2023.e17140

Oswald, M., Grace, J., Urwin, S., & Barnes, G. C. (2018). Algorithmic risk assessment policing models: Lessons from the Durham HART model and 'Experimental' proportionality. Information & Communications Technology Law, 27(2), 223– 250. https://doi.org/10.1080/13600834.2018.1458455

Pasha, S. A., Ali, S., & Jeljeli, R. (2022). Artificial Intelligence Implementation to Counteract Cybercrimes Against Children in Pakistan. Human Arenas. https://doi.org/10.1007/s42087-022-00312-8

Peter, D. (2022). Facial recognition technology for policing and surveillance in the Global South: A call for bans. Third World Quarterly, 43, 1– 11. https://doi.org/10.1080/01436597.2022.2080654

Piraianu, A.-I., Fulga, A., Musat, C. L., Ciobotaru, O.-R., Poalelungi, D. G., Stamate, E., Ciobotaru, O., & Fulga, I. (2023). Enhancing the Evidence with Algorithms: How Artificial Intelligence Is Transforming Forensic Medicine. Diagnostics, 13(18), 2992. https://doi.org/10.3390/diagnostics13182992

Putera, N. S. F. M. S., Saripan, H., Bajury, M. S. A., & Ya'cob, S. N. (2022). Artificial Intelligence-Powered Criminal Sentencing in Malaysia: A conflict with the rule of law. International Virtual Colloquium on Multi-disciplinary Research Impact (2nd Series). file:///C:/Users/Dell%20Inspiron/Downloads/eiph,+3813_xmp.pdf

Rodrigues, R. (2020). Legal and human rights issues of AI: Gaps, challenges and vulnerabilities. Journal of Responsible Technology, 4, 100005. https://doi.org/10.1016/j.jrt.2020.100005

Sachoulidou, A. (2023). Going beyond the "common suspects": To be presumed innocent in the era of algorithms, big data and

Article DOI: https://doi.org/10.37284/eajit.7.1.2141

artificial intelligence. Artificial Intelligence and Law. https://doi.org/10.1007/s10506-023-09347-w

Schuilenburg, M., & Soudijn, M. (2023). Big data policing: The use of big data and algorithms by the Netherlands Police. Policing: A Journal of Policy and Practice, 17, paad061. https://doi.org/10.1093/police/paad061

Seseni, L., Thaba, S., Mbohwa, C., & Madonsela, N. (2023, July 18). Smart Cities as a Vehicle to addressing Sustainable Development Goals in South Africa. https://doi.org/10.46254/EU6.20230285

Shrivastava, A. (2023). Data Science/ AI: A Possible Panacea for Refugee Crisis. Journal of Student Research, 11. https://doi.org/10.47611/jsrhs.v11i3.2973

Singh, D. (2022). Policing by Design: Artificial Intelligence, Predictive Policing and Human Rights in South Africa. Just Africa, 7(1), 41–52. https://doi.org/10.10520/ejc- ajcj_v7_n1_a7

Singh, S., & Nambiar, V. (2024). Role of Artificial Intelligence in the Prevention of Online Child Sexual Abuse: A Systematic Review of Literature. Journal of Applied Security Research, 1– 42. https://doi.org/10.1080/19361610.2024.2331885

Söderholm, S. (2023). Fundamental rights control when implementing predictive policing – a European perspective. Peking University Law Journal, 11(1), 91– 104. https://doi.org/10.1080/20517483.2023.2223850

Spivak, B. L., & Shepherd, S. M. (2021). Ethics, Artificial Intelligence, and Risk Assessment. Journal of the American Academy of Psychiatry and the Law Online. https://doi.org/10.29158/JAAPL.210066-21

Steden, R., Wood, J., Shearing, C., & Boutellier, H. (2013). The Many Faces of Nodal Policing: Team Play and Improvisation in Dutch Community Safety. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.2674009

Stockhem, O. (2020). Improving the regulation of cybersex trafficking of women and children through the use of data science and artificial intelligence.

Strikwerda, L. (2021). Predictive policing: The risks associated with risk assessment. The Police Journal, 94(3), 422– 436. https://doi.org/10.1177/0032258X20947749

Subramani, S., Wang, H., Islam, M. R., Ulhaq, A., & O'Connor, M. (2018). Child Abuse and Domestic Abuse: Content and Feature Analysis from Social Media Disclosures (pp. 174–185). https://doi.org/10.1007/978-3-319-92013-9_14

Sunde, I. M. (2022). AI-based Law Enforcement Online: The Impact of the European Artificial Intelligence Act (AIA). Bergen Journal of Criminal Law & Criminal Justice, 10, 29–50. https://doi.org/10.15845/bjclcj.v10i2.3844

Swart, M. (2023). CoCT using gunshot detection and drones to pinpoint gang violence. https://www.capetownetc.com/news/gunshot-detection-pinpoint-gang-violence/

Thao, N. P. (2023). The Use of Artificial Intelligence in Criminal Investigation and Trials in Europe and Some Countries: Experience for Vietnam. Vietnamese Journal of Legal Sciences, 8(1), 55– 77. https://doi.org/10.2478/vjls-2023-0003

Urquhart, L., & Miranda, D. (2022). Policing faces: The present and future of intelligent facial surveillance. Information & Communications Technology Law, 31(2), 194– 219. https://doi.org/10.1080/13600834.2021.1994220

Van der Watt, M. (2023). Discouraging the Demand That Fosters Sex Trafficking: Collaboration through Augmented Intelligence. Societies, 13(4), Article 4. https://doi.org/10.3390/soc13040094

