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ARTIFICIAL INTELLIGENCE IN CRIMINAL JUSTICE MANAGEMENT: A SYSTEMATIC LITERATURE REVIEW

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ABSTRACT

This systematic review, based on 37 articles, explores the role of artificial intelligence (AI) in criminal justice, focusing on its applications in predictive policing, judicial risk assessments, and surveillance, as well as the associated ethical and regulatory challenges. AI has demonstrated substantial potential for improving efficiency and accuracy in criminal justice systems, from optimizing law enforcement resource allocation to providing data-driven risk assessments that support judicial decisions. However, the review identifies significant ethical issues, especially related to algorithmic bias, which can perpetuate existing societal inequalities and disproportionately affect marginalized communities. Concerns around transparency and accountability are prevalent, as the "black-box" nature of many AI algorithms complicates public understanding and trust in AI-driven outcomes. Surveillance tools, including facial recognition and behavioral analysis, enhance real-time threat detection but raise privacy and civil rights concerns, highlighting the need for regulatory oversight. Gaps in legal frameworks suggest the urgency for standardized policies that address data privacy, algorithmic fairness, and accountability in AI applications. The findings underscore that interdisciplinary collaboration, transparent practices, and comprehensive regulatory measures are essential to responsibly integrate AI into criminal justice, balancing technological advancements with justice, equity, and public trust.

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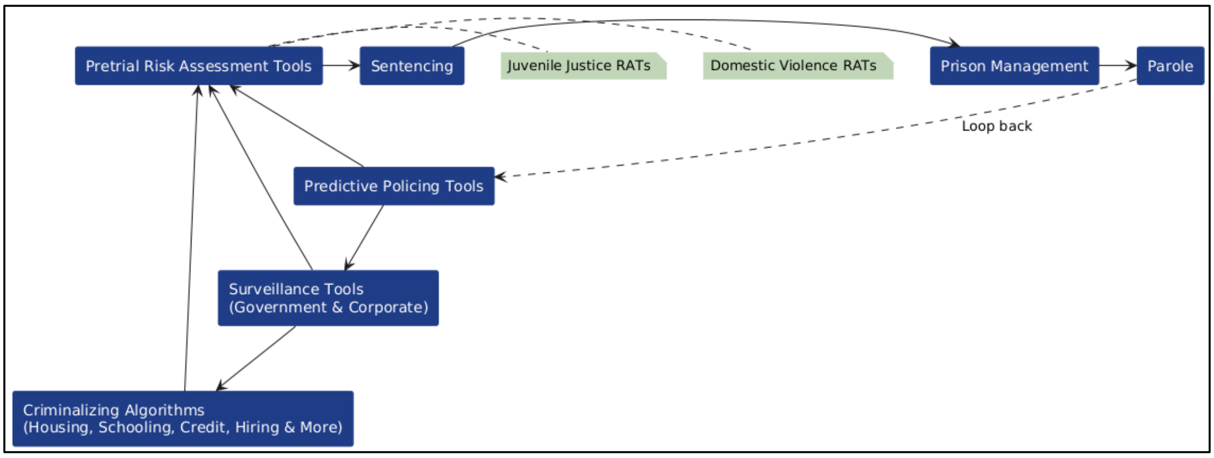
1 Introduction

Artificial intelligence (AI) has increasingly transformed criminal justice management by enabling novel ways to analyze data, forecast criminal activities, and support decision-making processes (Martin, 2018). AI technologies such as predictive policing algorithms, risk assessment tools, and surveillance systems have shifted how criminal justice institutions approach crime prevention and offender management. Early AI applications in criminal justice focused on straightforward data analysis, aimed at identifying crime patterns and hotspots. However, recent advancements in machine learning and big data analytics have expanded AI's utility, enabling complex decision support and predictive capabilities that drive efficiency and accuracy in crime prevention and criminal justice processes (Gless et al., 2016). This systematic literature review aims to synthesize how AI has evolved within the domain of criminal justice, highlighting the milestones achieved and addressing the challenges inherent in deploying AI-driven tools.
Over the years, criminal justice systems have been adopting quantitative methods to manage case backlogs and allocate resources effectively, but these approaches were limited in scope and predictive power (Egbert & Leese, 2020). The surge of big data and machine learning has introduced possibilities to automate crime analysis and enhance accuracy, particularly in predictive policing. Predictive policing is one of the earliest implementations of AI in criminal justice, using historical crime data, environmental factors, and socio-demographic variables to forecast potential crime hotspots (Završnik, 2020). Studies on predictive policing have shown improvements in resource allocation and police response times (Campbell, 2013; Završnik, 2020); however, scholars caution against potential biases in the data used, which can lead to discriminatory targeting of specific communities (Završnik, 2020). These concerns have prompted a critical examination of predictive policing's evolution from simple data-driven forecasting to more nuanced and complex AI models, reflecting both the promise and the ethical dilemmas AI poses in criminal justice (Wu & Zhang, 2016; Završnik, 2020).
In addition to predictive policing, AI has found applications in judicial decision-making through risk assessment tools designed to aid judges in evaluating the risks associated with bail, parole, and sentencing decisions. Tools like COMPAS (Correctional Offender Management Profiling for Alternative Sanctions) have demonstrated utility in informing judges by predicting the likelihood of reoffending, based on historical data and offender profiles (Gless et al., 2016). While these tools are intended to enhance judicial consistency and mitigate bias, there is evidence that AI-based assessments may inadvertently perpetuate racial or socio-economic biases present in historical data (Dement & Inglis, 2024; Sohel et al., 2024; Uddin, Auyon, et al., 2024; Uddin, Ullah, et al., 2024). Research indicates that these biases can have profound implications for fairness in judicial outcomes, with some studies urging for greater transparency and explainability in AI algorithms used in the judicial system (Alam et al., 2024; Badhon et al., 2023; Simmons, 2016). The evolution of AI in judicial decision-making has thus raised essential ethical questions, pushing for frameworks to ensure that AI-

Figure 1:AI Integration in Criminal Justice: A Lifecycle of Tools and Technologies



supported decisions align with principles of justice and equity.

AI-driven surveillance technologies have also become central to criminal justice, with video analytics and facial recognition systems enhancing the ability to monitor large areas and track potential criminal activities (Simmler et al., 2022). These technologies allow law enforcement agencies to detect and analyze patterns in real-time, providing faster responses and potential prevention of criminal acts (Simmler, 2021). Despite their operational advantages, AI-based surveillance systems have spurred debates about privacy violations and ethical use, especially given their potential for misuse in profiling or unauthorized monitoring (Simmler et al., 2021). The tension between operational efficiency and individual privacy rights highlights the need for clear ethical guidelines and legal frameworks governing AI's use in surveillance. Scholars advocate for regulated, transparent use of AI surveillance tools to safeguard civil liberties while benefiting from technological advances (Simmons, 2016).

As AI applications have grown more sophisticated, the complexity of ethical, legal, and technical challenges has likewise increased. The progressive adoption of AI in criminal justice has necessitated multi-disciplinary approaches to address issues such as algorithmic transparency, bias mitigation, and the ethical deployment of technology in sensitive contexts (Simmler et al., 2022). Interdisciplinary collaborations involving technologists, policymakers, criminal justice professionals, and legal scholars have emerged as essential in understanding and navigating these complexities. (Simmons, 2016) emphasize that, for AI to truly support justice, it must be developed with careful consideration of fairness and accountability, embedding these principles within the technology's design and implementation. Such an approach to AI in criminal justice underscores the importance of evolving not only the technology itself but also the frameworks within which it operates, ensuring it advances social good while respecting civil rights. This systematic literature review aims to explore and critically examine the evolving role of artificial intelligence in criminal justice management. Specifically, the review seeks to analyze how AI applications have transformed operational processes in areas such as predictive policing, judicial decision-making, and surveillance, while also identifying the ethical, legal, and social implications associated with these advancements. By systematically evaluating existing research, this study intends to assess the effectiveness, challenges, and limitations of AI tools within criminal justice, providing a comprehensive overview of both benefits and potential risks. Furthermore, the review will identify key trends and research gaps to inform future studies and encourage the development of ethical frameworks and transparent practices in AI deployment. Ultimately, the objective is to synthesize current knowledge on AI in criminal justice, fostering a balanced understanding of its impact and guiding responsible innovation in the field.

2 Literature Review

The application of artificial intelligence in criminal justice management has garnered substantial scholarly attention, reflecting both the promise and challenges inherent in leveraging AI for complex decision-making processes. This literature review section delves into existing research on the role of AI in criminal justice, examining its contributions to predictive policing, judicial support systems, surveillance, and ethical considerations. With the rapid evolution of AI technology, various studies have highlighted the advantages AI brings to criminal justice, such as enhancing accuracy and operational efficiency. However, concerns about algorithmic bias, privacy violations, and the ethical implications of AI-driven decisions are also prominent. This section provides a structured review of relevant studies, organized by key thematic areas that illustrate the multifaceted impact of AI in criminal justice management. The aim is to synthesize findings across different domains, critically assess the benefits and risks, and identify research gaps for future inquiry.

2.1 Introduction to AI in Criminal Justice

Artificial intelligence (AI) has increasingly reshaped the landscape of criminal justice, bringing transformative potential in areas like predictive policing, judicial decision-making, and surveillance (Dement & Inglis, 2024). Through predictive analytics and data-driven models, AI has allowed criminal justice agencies to process vast amounts of data and identify patterns that were previously challenging to detect (Plesničar et al., 2020). For instance, predictive policing uses historical crime data to forecast potential crime hotspots, enabling

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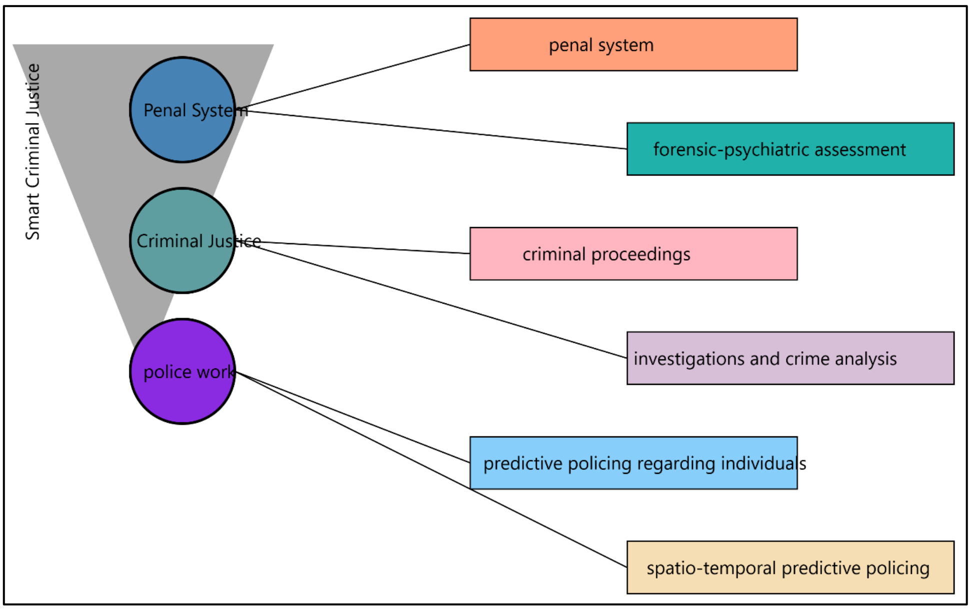
law enforcement agencies to allocate resources more efficiently (Lum & Isaac, 2016). However, while AI offers potential for enhancing operational efficiency, scholars have raised concerns about the risks of reinforcing biases present in historical data, potentially impacting marginalized communities disproportionately (Gless et al., 2016; Simmons, 2016). The scope of this literature review will focus on synthesizing research across these applications and examining both the potential benefits and ethical challenges that arise from AI use in criminal justice management.

Predictive policing, one of the most widely adopted AI applications in criminal justice, leverages machine learning algorithms and historical crime data to make proactive decisions about resource allocation and patrol routes (Finlay, 2014). Studies demonstrate that predictive policing can be effective in preventing crime by allowing law enforcement to respond swiftly to emerging crime patterns (Perry et al., 2013). However, predictive models often rely on data embedded with societal biases, which may result in unequal targeting of certain demographics, as studies by (Sommerer, 2020) and (Cavelty & Hagmann, 2021) indicate. (Egbert & Krasmann, 2019) argue that without rigorous ethical frameworks, predictive policing could inadvertently contribute to systemic biases. These issues highlight the need for transparent and accountable AI models, as well as continued evaluation to ensure fair and unbiased implementation (Perry et al., 2013). In judicial decision-making, AI has been adopted to support judges in assessing the risk of recidivism, parole decisions, and bail settings (Kadar et al., 2019). Tools like COMPAS (Correctional Offender Management Profiling for Alternative Sanctions) have been implemented in courts to assist in predicting reoffending risks, aiming to improve consistency and impartiality in judicial decisions (Siegel, 2013). Yet, studies reveal that these tools are not immune to biases within the data used, raising ethical concerns regarding fairness and transparency in the judiciary (Llinares, 2020). Although AI systems can improve efficiency, research by (Kadar et al., 2019) emphasizes the importance of incorporating ethical safeguards to avoid reinforcing racial or socioeconomic biases. As these systems become integral to judicial processes, it is crucial to balance technological benefits with a commitment to justice and equity (Shapiro, 2017).

AI-driven surveillance, including video analytics and facial recognition, has become increasingly common in law enforcement, enabling real-time monitoring and the identification of individuals and behaviors that may indicate criminal activity (Llinares, 2020). While these technologies offer significant potential for crime prevention, they also pose privacy and ethical concerns, especially regarding the potential for misuse or non-consensual surveillance (Simmons, 2016). Scholars like (Kadar et al., 2019) and (Siegel, 2013) argue that the use of facial recognition technologies without appropriate regulations can infringe upon civil liberties, calling for clear legal and ethical guidelines. Overall, as the role of

Figure 2: Smart Criminal Justice Framework



AI in criminal justice expands, studies underscore the need for interdisciplinary collaboration and ethical standards to guide responsible and equitable implementation (Benbouzid, 2019).

2.2 Historical Context and Development

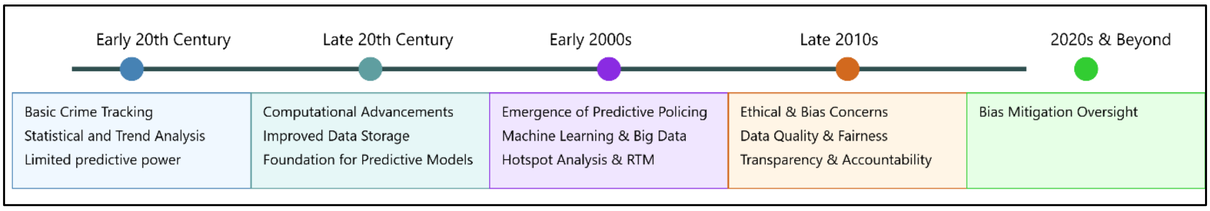
The integration of data analysis in crime prevention began in the early 20th century, where crime data was used primarily for statistical tracking and trend analysis (Berk, 2021). Early methods were simplistic, relying heavily on traditional crime reports and basic trend analysis to determine patterns in criminal activities. These methods provided useful insights for police departments but were limited in scope and lacked the predictive power to foresee crime locations or times with precision (Tolan et al., 2019). As digital technology advanced, so did the collection and analysis of crime-related data, laying the groundwork for more sophisticated data-driven approaches. By the late 20th century, computational techniques allowed for enhanced data storage and processing, setting the stage for the development of predictive policing models (Saunders et al., 2016).

Predictive policing emerged as a field in the early 2000s, fueled by advancements in machine learning and big data analytics, which enabled more precise crime forecasting by leveraging historical data (Finlay, 2014). Predictive policing models like hotspot analysis and risk terrain modeling use various data points—such as crime locations, times, and demographic information—to predict where crimes are likely to occur (Cavelty & Hagmann, 2021). These models initially focused on geographic crime prediction, aiming to assist police departments in efficiently deploying resources. Studies by Simmons (2016) and Benbouzid (2019) found that predictive policing had the potential to improve crime response times and resource allocation, helping law enforcement to be more proactive. However, as studies by Sandhu and Fussey (2020) and Egbert (2018) pointed out, the effectiveness of these models depends heavily on the quality and fairness of the data used, as biased data can reinforce systemic inequalities.

Despite its promise, predictive policing has faced considerable criticism regarding the biases that may arise from historical crime data. Scholars argue that because crime data reflects past policing practices, which may be influenced by social and racial biases, predictive policing models can inadvertently reinforce these biases (Moses & Chan, 2016). For instance, Berk (2021) examined the potential for predictive policing to target minority communities disproportionately, as these models tend to prioritize areas with higher reported crime rates—often communities with greater law enforcement presence historically. Rummens and Hardyns (2021) argue that without transparency and safeguards, predictive models may perpetuate patterns of over-policing in specific neighborhoods, raising ethical concerns about fairness and justice in criminal justice practices.

Over the years, efforts have been made to address the ethical challenges of predictive policing by promoting transparency, accountability, and bias mitigation in predictive models (Cavelty & Hagmann, 2021). The need for more transparent algorithms has led to calls for interdisciplinary research and the development of regulatory frameworks that ensure fair use of predictive tools in policing (Saunders et al., 2016). Some studies have proposed using algorithms designed to reduce bias by adjusting for demographic variables or incorporating fairness constraints (Finlay, 2014; Shamim, 2022). While these approaches show promise, Egbert and Krasmann (2019) and Simmons (2016) emphasize the importance of continuous oversight and evaluation, arguing that predictive policing should be an aid to decision-making rather than a substitute for human judgment. Thus, while predictive policing represents a significant shift from traditional data analysis to a more advanced, proactive model, its ethical implications

Figure 3: Evolution of Predictive Policing Technologies



continue to be a focal point for researchers and practitioners alike.

2.3 Techniques and Algorithms Used in Predictive Policing

The rise of predictive policing has been largely driven by advancements in data analysis algorithms and machine learning techniques, allowing law enforcement agencies to forecast crime with greater accuracy and efficiency (Berk, 2021). Early predictive policing models utilized relatively simple statistical methods, such as hotspot analysis, which identifies areas with high crime density based on historical data (Cavelty & Hagmann, 2021). As technology advanced, these basic models were supplemented by more sophisticated machine learning algorithms, which can incorporate numerous variables and learn from large datasets to improve prediction accuracy over time (Brayne, 2020). Studies such as those by Finlay (2014) and Siegel (2013) demonstrate how machine learning's adaptability makes it well-suited to predict complex patterns in crime data, marking a shift from traditional statistical methods to more dynamic, data-intensive approaches in law enforcement.

A commonly used approach in predictive policing is regression analysis, particularly logistic and linear regression, which helps model relationships between crime occurrences and influencing factors such as location, time, and environmental variables (Rummens & Hardyns, 2021). Regression models are relatively easy to interpret and have been widely adopted in the early stages of predictive policing initiatives. However, research shows that these models may lack the flexibility required to capture non-linear relationships in crime data (Tolan et al., 2019). Machine learning algorithms, such as decision trees and random forests, offer solutions by building predictive models based on numerous features and adjusting as new data is introduced (Egbert, 2018). Rummens and Hardyns (2021) argue that these algorithms allow for more nuanced predictions by learning from the patterns in data rather than relying solely on historical trends, which can help in creating more accurate forecasts.

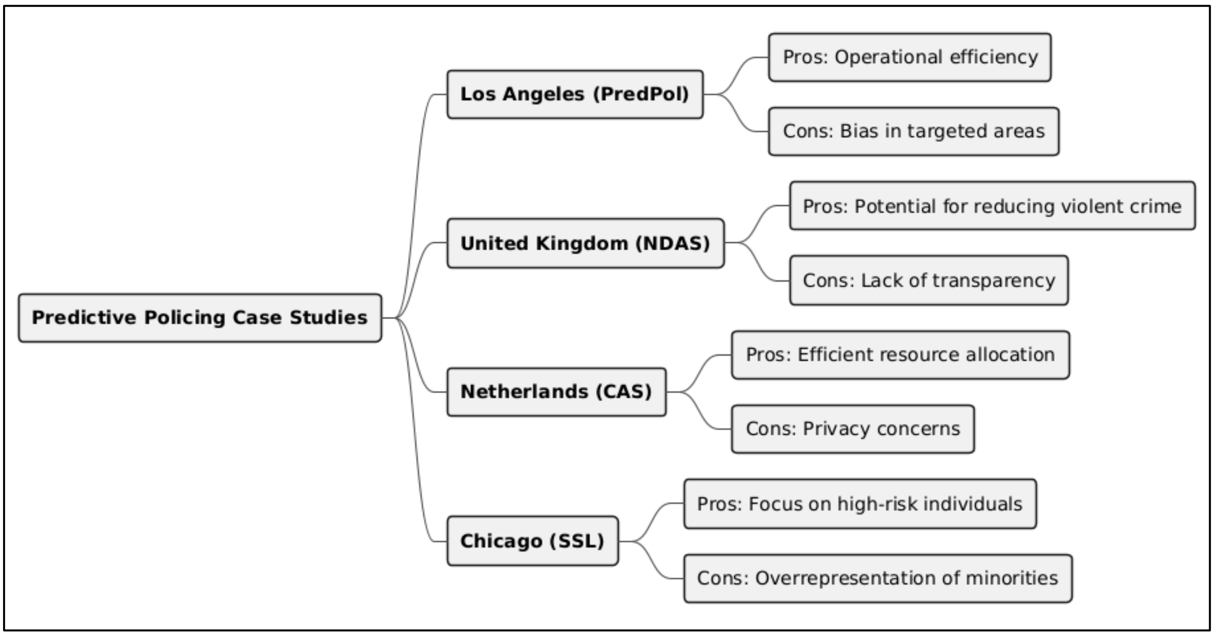
In recent years, more complex algorithms, including neural networks and deep learning models, have also been explored for crime prediction, as they can process vast amounts of data and identify intricate patterns that traditional methods might overlook (Tolan et al., 2019). Neural networks, inspired by the structure of the human brain, are particularly effective for recognizing patterns in unstructured data, such as text or images, which are increasingly used in surveillance and monitoring (Finlay, 2014). Studies by Simmons (2016) and Llinares (2020) show that deep learning techniques enable predictive policing systems to process multi-dimensional data inputs, including social media feeds and sensor data, which may add further context to crime prediction models. However, researchers also highlight the "black box" nature of neural networks, as the complex decision-making processes within these models can be challenging to interpret, raising questions about transparency and accountability (Benbouzid, 2019). In addition to neural networks, ensemble learning methods like random forests and gradient boosting have also gained popularity in predictive policing, as they combine multiple models to enhance prediction accuracy (Moses & Chan, 2016). These algorithms aggregate the outcomes of various individual models, reducing the likelihood of overfitting and improving robustness across different data sets (Berk, 2021). For example, Egbert and Leese (2020) emphasizes that ensemble methods are more resilient to data noise, making them suitable for the inherently uncertain nature of crime data. However, Tolan et al. (2019) caution that even advanced algorithms can be susceptible to biased data inputs, leading to discriminatory patterns if not carefully managed. As a result, the use of ensemble methods in predictive policing highlights the balance between technological sophistication and the ethical need for algorithmic fairness, a priority emphasized by Perry et al. (2013) and other scholars in the field.

2.4 Case Studies and Real-World Applications

Predictive policing has seen practical application in various cities and countries, each implementing the technology with different results and societal implications. One of the most cited case studies is Los Angeles, California, where the Los Angeles Police Department (LAPD) employed a predictive policing program known as PredPol, which uses algorithms to forecast crime hotspots based on historical crime data (Perry et al., 2013). Research on PredPol's effectiveness shows mixed results; while some studies suggest a reduction in crime incidents in targeted areas, others highlight concerns about data biases and unintended impacts on marginalized communities (Kadar et al., 2019). Benbouzid (2019) note that while PredPol provided LAPD with operational efficiencies, it also drew criticism for amplifying police presence in historically over-policed neighborhoods, which may perpetuate cycles of distrust and inequity.

In the United Kingdom, predictive policing was piloted in the Greater London area through the National Data Analytics Solution (NDAS), which combines machine learning with crime data to predict violent crime risk and identify potential offenders (Finlay, 2014). Studies on the NDAS indicate that the model shows potential for reducing violent crime, but scholars like Ferguson (2017) emphasize the importance of ethical safeguards to prevent misuse and maintain public trust. The NDAS model's outcomes sparked debates on transparency and accountability, especially regarding the algorithm's predictive criteria, which are not fully disclosed to the public (Uchida, 2014). The British experience underscores the need for transparency in predictive policing systems to address the ethical concerns associated with algorithmic governance and its implications for civil rights (Saunders et al., 2016). In Europe, the Netherlands has adopted predictive policing through the Crime Anticipation System (CAS), implemented in cities like Amsterdam and Rotterdam, where law enforcement uses predictive analytics to deploy resources in areas identified as high-risk (Cavelty & Hagmann, 2021). Studies conducted on CAS indicate that while it has enabled more efficient resource allocation and timely crime prevention, issues of privacy and the potential for discriminatory practices remain (Lum & Isaac, 2016). For instance, Simmons (2016) and Berk (2021) argue that CAS, similar to other predictive policing models, might inadvertently reinforce biases inherent in historical data, leading to increased surveillance in specific communities. The Dutch model highlights both the operational benefits of predictive policing and the ethical imperatives surrounding privacy and fair treatment, as researchers call for periodic evaluations and community involvement to ensure fair use (Eubanks, 2018). Chicago, Illinois, also experimented with predictive policing through its Strategic Subjects List (SSL), an algorithmic tool designed to identify individuals at high risk of becoming involved in gun violence, either as victims or perpetrators (Rummens & Hardyns, 2021). The outcomes of the SSL program, however, raised significant concerns, as studies found limited evidence of crime reduction and noted an overrepresentation of minority individuals on the list (Kehl & Kessler, 2017). Research by Wu and Zhang (2016) and Završnik (2020) suggests that SSL's focus on high-risk individuals rather than areas led to ethical challenges, as it may have contributed to stigmatizing certain populations without substantial evidence of crime prevention. This case underscores the complexities in individual-focused predictive policing models, pointing to the importance of balancing crime prevention with considerations for fairness and accountability, as emphasized by Campbell (2013) and Gless et al.(2016).

Figure 4: Predictive Policing Case Studies Overview



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2.5 Judicial Decision-Making and AI-Assisted Risk Assessments

Artificial intelligence has increasingly permeated judicial processes, with its applications spanning risk assessments, bail decisions, and sentencing recommendations (Plesničar et al., 2020). By employing machine learning algorithms and data-driven models, AI is designed to provide judges with insights that may improve consistency and impartiality in decision-making (Dement & Inglis, 2024). A prominent example is the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) tool, widely used in the United States to assess the likelihood of recidivism among defendants. Research by Shi (2022) demonstrates that COMPAS and similar AI-based tools can help streamline judicial processes by generating standardized assessments based on historical data and offender profiles. However, studies have raised concerns about the transparency and ethical implications of these models, as data biases may inadvertently influence judicial outcomes (Završnik, 2019).

AI-driven tools in judicial processes also play a significant role in bail decision-making, aiming to help judges evaluate flight risk and the probability of reoffending if a defendant is released (Velasco, 2022). In theory, such tools can promote fairness by reducing subjective judgment and providing a standardized assessment of each case (Završnik, 2020). However, several studies suggest that these AI systems may unintentionally reinforce existing biases present in historical data, potentially resulting in discriminatory practices (Plesničar et al., 2020; Velasco, 2022). For example, in jurisdictions where certain communities are disproportionately policed, AI models trained on local data may predict a higher risk for defendants from these communities, potentially leading to unfair bail decisions (Clark, 2013). This issue has led to growing calls for more transparent algorithms and ethical oversight in the deployment of AI in judicial contexts (Dupont et al., 2018). In sentencing, AI tools have been adopted to assist judges in determining the appropriate punishment for convicted individuals, with the intention of enhancing consistency and fairness (Završnik, 2019). Tools like COMPAS have been employed to estimate recidivism risk scores, which may influence sentencing severity, probation terms, or rehabilitation recommendations (Kotsoglou & Oswald, 2020). Although AI models can improve the efficiency of sentencing processes, researchers such as Simmons (2016) argue that these models may not adequately capture the complexities of individual cases. For instance, Stewart (2013) conducted studies showing that human judgment often differs from AI recommendations, highlighting the potential limitations of relying solely on algorithmic outputs. Consequently, scholars emphasize that AI should serve as an aid, not a substitute, in judicial decision-making to avoid oversimplification of complex sentencing considerations (Simmler, 2021). The ethical implications of AI in judicial decision-making underscore the need for accountability, transparency, and fairness. Kehl and Kessler (2017) argue that AI algorithms used in the justice system should be subject to rigorous evaluation and continuous monitoring to ensure they do not exacerbate racial or socioeconomic biases. Shi (2022) advocates for greater transparency in the algorithms' design and use, enabling judicial officers, defendants, and the public to better understand how decisions are reached. These perspectives align with the growing demand for ethical frameworks and interdisciplinary collaboration in AI deployment within judicial processes (Završnik, 2020). As AI tools continue to evolve, researchers agree that they must be designed and implemented with careful consideration of their potential impact on justice and equity, particularly in high-stakes areas like judicial risk assessments and sentencing (Campbell, 2013).

2.6 Commonly Used Risk Assessment Tools

In recent years, tools like the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) and the Public Safety Assessment (PSA) have become widely adopted in judicial systems to aid in assessing defendants' risk levels for reoffending or failing to appear in court (Campbell, 2013; Wu & Zhang, 2016). These tools utilize various algorithms that analyze historical data, personal background, and case details to assign risk scores, which are then used by judges during bail, parole, and sentencing decisions. COMPAS, in particular, has been noted for its capacity to standardize the assessment process, reducing potential inconsistencies from subjective judgment (Završnik, 2020). However, while these tools can enhance efficiency and consistency, studies have raised questions about their transparency and the potential biases embedded in their algorithms (Gless et al., 2016).

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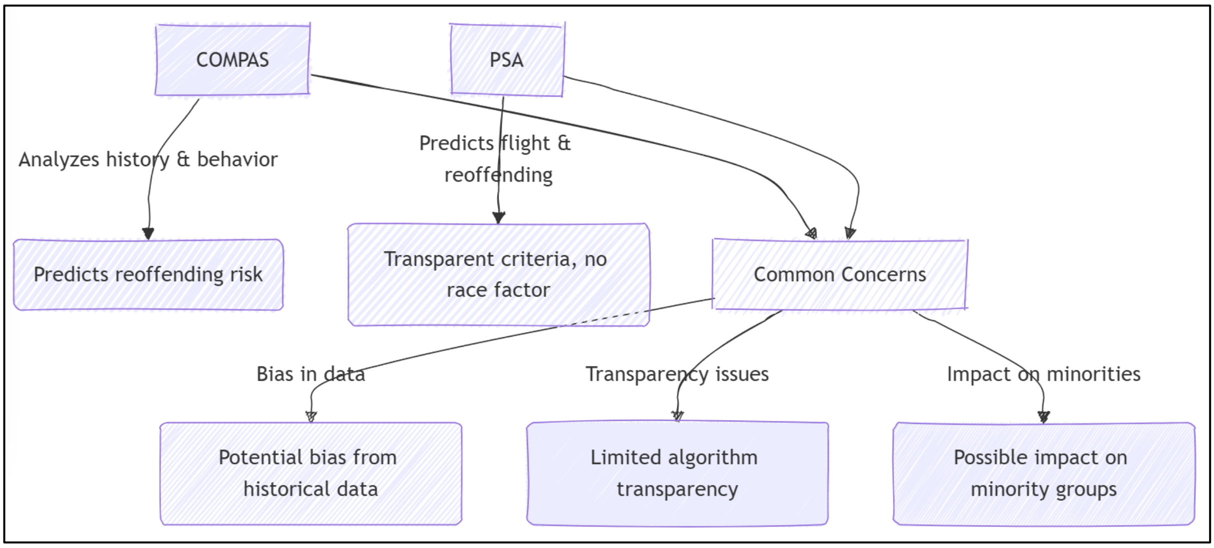
COMPAS evaluates factors like prior criminal history, socioeconomic background, and behavioral indicators to determine a risk score, which indicates the likelihood of reoffending (Shi, 2022). Although COMPAS has gained popularity for its structured approach, studies reveal significant concerns regarding its accuracy and potential bias, especially toward minority groups (Schulhofer, 1988). Research by Plesničar et al. (2020) and Završnik (2020) has shown that risk scores may disproportionately classify minority defendants as high-risk, even when their criminal histories are comparable to non-minorities. These findings suggest that COMPAS may reinforce existing racial disparities, as its algorithms are trained on historical data that may reflect systemic biases in law enforcement (Kotsoglou & Oswald, 2020). Thus, scholars argue for more scrutiny and transparency in the design and use of such risk assessment tools (Ferguson, 2017).

The Public Safety Assessment (PSA), developed by the Laura and John Arnold Foundation, is another widely used tool, focusing primarily on flight risk and the likelihood of reoffending for defendants awaiting trial (Dupont et al., 2018). Unlike COMPAS, PSA does not consider race or socioeconomic variables directly, instead assessing factors such as previous court appearances, age, and criminal history (Wu & Zhang, 2016). Studies have noted that PSA's emphasis on objective factors may reduce certain biases, although researchers caution that indirect biases may still manifest through other variables (Chen et al., 2004). PSA has been praised for its transparency, with the foundation openly sharing its assessment criteria, yet scholars like Završnik (2020) emphasize the importance of periodic evaluations to ensure PSA's efficacy and fairness across different demographics and judicial settings.

The effectiveness of tools like COMPAS and PSA is still a subject of debate, as both models present unique strengths and challenges in risk assessment. For instance, Velasco (2022) found that while COMPAS can be useful for quickly categorizing high-risk offenders, its accuracy may not significantly surpass simpler methods or even human judgment. Similarly, PSA has shown promise in providing consistent risk assessments, but its dependence on prior criminal activity and other background factors may inadvertently impact individuals from communities with higher rates of policing (Kotsoglou & Oswald, 2020). These insights highlight the ongoing need for balanced evaluations that consider both the quantitative performance of these tools and their broader societal impacts (Završnik, 2020). Overall, studies indicate that while COMPAS and PSA contribute valuable support to judicial decision-making, their design and implementation must be carefully managed to avoid unintentional biases or inequities. Scholars advocate for increased transparency and accountability in how these tools function and influence judicial outcomes, as well as for regular algorithmic audits and ethical reviews (Campbell, 2013). As AI-driven risk assessment tools continue to evolve, it is essential to address their limitations and potential biases, ensuring they enhance rather than

Figure 5:Commonly Used Risk Assessment Tools



undermine justice and fairness in the legal system contexts(Plesničar et al., 2020).

2.7 Facial Recognition and Behavioral Analysis Technologies

Artificial intelligence (AI) has significantly advanced facial recognition and behavioral analysis technologies, becoming integral tools in modern law enforcement. Facial recognition systems utilize AI algorithms to identify individuals by analyzing facial features from images or video footage, comparing them against databases of known faces to find matches (Wu & Zhang, 2016). These systems have been employed in various contexts, such as identifying suspects, locating missing persons, and enhancing security measures in public spaces (Završnik, 2019). Behavioral analysis technologies, on the other hand, assess patterns in human behavior, including movement and social interactions, to detect anomalies that may indicate criminal activity (Clark, 2013). The integration of these AI-driven tools aims to augment the capabilities of law enforcement agencies, enabling more proactive and efficient responses to crime.

The deployment of facial recognition technology in law enforcement has been widespread, with agencies utilizing it for real-time surveillance and post-event investigations. For instance, the New York Police Department (NYPD) has implemented facial recognition to match images from crime scenes with mugshot databases, aiding in suspect identification (Završnik, 2020). Similarly, the London Metropolitan Police have conducted trials using live facial recognition cameras to monitor public events and identify individuals on watchlists (Gless et al., 2016). While these applications have demonstrated potential in enhancing public safety, studies have raised concerns regarding accuracy and potential biases. Research indicates that facial recognition systems may exhibit higher error rates for certain demographic groups, particularly women and people of color, leading to false positives and potential wrongful identifications (Shi, 2022; Wu & Zhang, 2016). These findings underscore the need for rigorous testing and validation of AI algorithms to ensure fairness and reliability in law enforcement applications.

Behavioral analysis technologies complement facial recognition by focusing on patterns of behavior that may signal criminal intent or activity. AI systems analyze data from various sources, including surveillance footage, social media, and communication networks, to identify behaviors deviating from established norms (Schulhofer, 1988). For example, AI-driven tools can monitor crowd dynamics to detect unusual movements or gatherings that could indicate potential threats (Campbell, 2013). Additionally, predictive analytics models assess historical crime data and social patterns to forecast potential criminal hotspots, enabling law enforcement to allocate resources more effectively (Završnik, 2020). However, the implementation of behavioral analysis technologies raises ethical and privacy concerns, as continuous monitoring and data collection may infringe upon individual rights and civil liberties (Gless et al., 2016). Scholars advocate for transparent policies and oversight mechanisms to balance the benefits of these technologies with the protection of fundamental rights (Clark, 2013).

The integration of facial recognition and behavioral analysis technologies in law enforcement presents both opportunities and challenges. On one hand, these AI-driven tools offer enhanced capabilities for crime detection and prevention, potentially leading to safer communities (Dement & Inglis, 2024). On the other hand, issues related to accuracy, bias, privacy, and ethical considerations necessitate careful implementation and oversight (Završnik, 2020). Researchers emphasize the importance of developing clear guidelines and regulatory frameworks to govern the use of AI in law enforcement, ensuring that technological advancements do not compromise justice and equity (Plesničar et al., 2020; Velasco, 2022). Ongoing interdisciplinary collaboration among technologists, legal experts, policymakers, and community stakeholders is essential to navigate the complexities associated with AI applications in the criminal justice system (Dement & Inglis, 2024).

2.8 Regulatory and Legal Frameworks

The rapid adoption of AI-driven surveillance technologies in law enforcement has prompted calls for robust regulatory and legal frameworks to ensure responsible use and protect civil liberties (Shi, 2022). In recent years, several countries have attempted to establish guidelines and laws to govern AI surveillance, reflecting a growing recognition of the ethical, privacy, and human rights concerns associated with these technologies (Wu & Zhang, 2016). The European Union, for example, has introduced comprehensive privacy laws such as the General Data Protection

Regulation (GDPR), which emphasizes data protection, consent, and transparency (Završnik, 2020). The GDPR is a landmark regulation that holds AI surveillance systems accountable for how data is collected, processed, and stored, setting a precedent for countries worldwide. This approach highlights the importance of clear guidelines for AI in public and private surveillance, aiming to safeguard citizens from potential misuse.

In the United States, regulatory responses to AI surveillance remain fragmented, with a combination of federal and state-level initiatives addressing aspects of AI governance (Velasco, 2022). The absence of a federal standard has led states like California and Illinois to implement specific regulations on facial recognition and AI-based data collection (Dement & Inglis, 2024). California's Consumer Privacy Act (CCPA), for example, provides individuals with rights over their personal data, allowing them to know, delete, or restrict its use (Završnik, 2020). While these regulations attempt to fill gaps at the state level, studies argue that the lack of uniform national policy leaves significant room for variance in AI application, often leading to regulatory inconsistencies (Clark, 2013). This patchwork approach has raised concerns about fairness and accountability, underscoring the need for standardized regulations that encompass AI-driven surveillance practices across the country. Several scholars emphasize the need for accountability and transparency as key elements in AI surveillance frameworks (Plesničar et al., 2020). Velasco (2022) and Dement and Inglis (2024) argue that without stringent transparency requirements, AI surveillance tools could operate without public scrutiny, leading to issues such as wrongful identification or biased surveillance. Recent initiatives aim to incorporate algorithmic accountability, where law enforcement agencies are required to disclose the decision-making processes behind AI-driven tools, including their accuracy rates, biases, and data sources (Campbell, 2013). In the European Union, the proposed Artificial Intelligence Act builds on GDPR principles, targeting high-risk AI applications and introducing requirements for testing, auditing, and risk assessment in surveillance tools (Shi, 2022). This development reflects a growing consensus that transparency is essential for fair and equitable AI governance, especially in sectors like law enforcement where public trust is paramount.

2.9 Algorithmic Bias and its Social Implications

The integration of artificial intelligence (AI) into criminal justice systems has raised significant concerns regarding algorithmic bias and its impact on marginalized communities. Studies have demonstrated that AI algorithms, particularly those used in predictive policing and risk assessments, can perpetuate existing societal biases present in historical crime data (Egbert & Leese, 2020; Shi, 2022; Wu & Zhang, 2016). For instance, Završnik (2020) found that predictive policing models often disproportionately target minority neighborhoods, leading to over-policing and reinforcing negative stereotypes. This phenomenon occurs because these algorithms are trained on historical data that may reflect systemic biases, resulting in discriminatory outcomes against marginalized groups (Plesničar et al., 2020). In judicial contexts, risk assessment tools like COMPAS have been scrutinized for their potential to produce biased results. Schermer et al. (2019) revealed that COMPAS scores were more likely to incorrectly label Black defendants as high-risk compared to their white counterparts, raising concerns about fairness and equity in sentencing and bail decisions. Similarly, Chen et al. (2004) found that these tools did not significantly outperform human judgment and often reflected existing prejudices. These findings suggest that reliance on such AI systems without addressing underlying biases can exacerbate disparities in the criminal justice system (Kehl & Kessler, 2017).

The social implications of algorithmic bias extend beyond individual cases, influencing public perceptions and trust in law enforcement and judicial institutions. Hannah-Moffat (2018) argues that the use of biased AI tools can legitimize discriminatory practices, leading to a cycle of marginalization for affected communities. Moreover, Dupont et al. (2018) highlights that the lack of transparency in AI decision-making processes makes it challenging for individuals to contest unfair outcomes, thereby undermining procedural justice. These issues underscore the need for greater accountability and oversight in the deployment of AI technologies within criminal justice (Shi, 2022). Addressing algorithmic bias requires a multifaceted approach, including the development of fairer algorithms, comprehensive bias audits, and inclusive policymaking. Researchers like Campbell (2013) advocate for the implementation of fairness constraints in AI models to mitigate discriminatory outcomes. Additionally, Plesničar et al.

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(2020)emphasize the importance of involving diverse stakeholders in the design and evaluation of AI systems to ensure they serve all communities equitably. As AI continues to play a pivotal role in criminal justice, it is imperative to confront and rectify algorithmic biases to promote justice and uphold human rights (Brayne, 2020).

2.10 Synthesis of Findings and Identification of Research Gaps

The review of literature on AI applications in criminal justice reveals both significant advancements and critical areas that require further investigation, particularly concerning transparency, interdisciplinary collaboration, and public policy. Numerous studies have highlighted the effectiveness of AI in improving decision-making and efficiency in law enforcement, judicial risk assessments, and predictive policing (Dement & Inglis, 2024; Kehl & Kessler, 2017; Završnik, 2019). However, the lack of transparency in algorithmic processes remains a major concern, as the "black-box" nature of AI systems often obscures how decisions are made (Dupont et al., 2018). Scholars such as Dupont et al., (2018) argue that without clear explanations of AI-driven decisions, it becomes difficult to ensure accountability, especially when these tools impact high-stakes outcomes like sentencing and bail. As a result, calls for transparency are gaining momentum, but frameworks for achieving it within criminal justice AI applications are still limited. Another gap identified in the literature is the need for interdisciplinary collaboration in the development and oversight of AI technologies used in criminal justice. Hannah-Moffat (2018) and Završnik (2020) emphasize that effective AI implementation in this field requires input from technologists, criminologists, legal experts, and ethicists to balance technological advancements with ethical considerations and social justice. Yet, studies indicate that the criminal justice sector often relies solely on technical expertise, leading to outcomes that may overlook social and legal implications (Velasco, 2022). The inclusion of diverse perspectives could foster AI systems that are not only technically robust but also sensitive to the complex social dynamics within criminal justice settings (Simmons, 2016). This collaborative approach is essential for addressing bias, transparency, and ethical concerns that arise in AI applications, though it remains underexplored in current research.

Table 1: Summary table of Research gaps

Key Areas	**Findings**	**Research Gaps**
Advancements in AI for Criminal Justice	AI has improved decision-making efficiency in areas like law enforcement, risk assessments, and predictive policing.	Need for frameworks to improve transparency and explainability in AI decisions within criminal justice.
Transparency in Algorithmic Processes	Lack of transparency in AI algorithms raises accountability concerns, especially in high-stakes decisions like sentencing.	Develop frameworks to ensure algorithmic accountability and clarity in AI-driven decision-making processes.
Interdisciplinary Collaboration	Effective AI deployment requires input from diverse fields, but reliance on technical expertise alone may overlook social and legal implications.	Incorporate insights from criminologists, legal experts, and ethicists alongside technical teams to create ethically robust AI systems.
Public Policy and Regulatory Frameworks	Few comprehensive policies exist to govern AI use in criminal justice; the EU GDPR is one example, but most countries lack specific frameworks.	Establish coordinated, specific policies for criminal justice AI, addressing privacy, data ownership, and accountability.

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Long-term Community Impact and Bias Mitigation	Algorithmic biases can perpetuate inequalities; limited research addresses how to mitigate long-term impacts on marginalized communities.	Further study required on mitigating algorithmic bias beyond technical solutions, addressing both immediate and systemic implications.

Public policy and regulatory frameworks also represent a significant research gap, as existing policies often lag behind rapid technological advancements in AI (Gless et al., 2016; Velasco, 2022). While regions like the European Union have begun establishing frameworks, such as the GDPR, to guide the ethical use of AI, most countries lack comprehensive policies specific to criminal justice applications (Hannah-Moffat, 2018; Shi, 2022). Scholars like Završnik (2020) advocate for regulations that specifically address issues of privacy, data ownership, and accountability in AI-driven criminal justice systems. The absence of uniform policies leaves a gap in the governance of AI in law enforcement, potentially leading to inconsistent practices and exacerbating concerns around fairness and rights protection (Plesničar et al., 2020). A coordinated policy approach that aligns technological innovation with legal safeguards is necessary to foster public trust and ensure ethical AI use. Finally, while AI in criminal justice has shown promise, the literature reveals a limited focus on the long-term impacts of these technologies on communities, particularly marginalized ones. Studies indicate that algorithmic biases can perpetuate inequalities in the criminal justice system, yet there is minimal research on mitigating these effects beyond technical fixes (Kehl & Kessler, 2017; Plesničar et al., 2020; Wu & Zhang, 2016). Researchers such as Richardson et al. (2019) and Ferguson (2017) underscore the need for policies that address both the immediate and systemic implications of AI adoption. This entails not only refining algorithms but also rethinking the social structures in which these technologies are deployed. The identification of these research gaps calls for a more holistic approach to studying AI in criminal justice, one that prioritizes transparency, interdisciplinary input, and comprehensive policy development to align AI technologies with ethical, equitable practices.

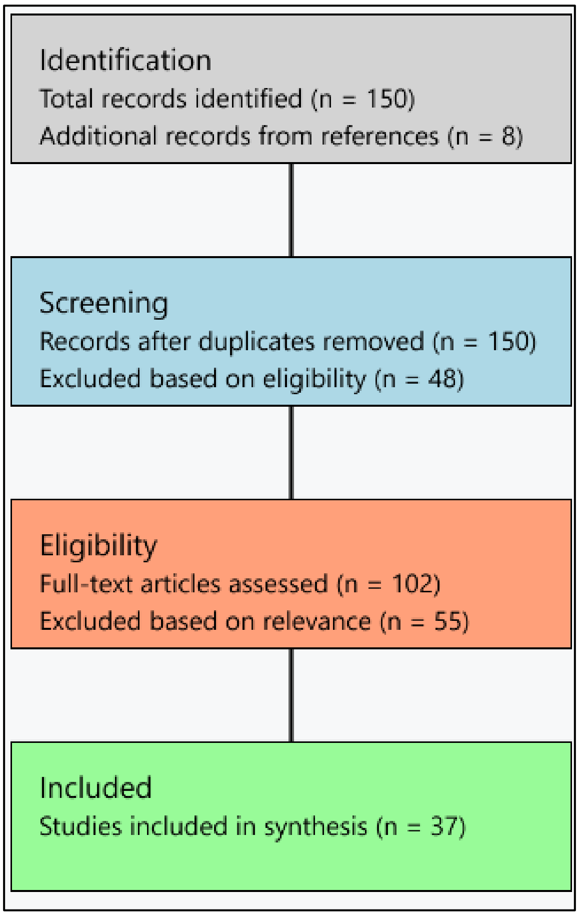
3 Method

This systematic literature review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines to ensure a rigorous, transparent, and comprehensive approach. Each step was conducted systematically, starting from an initial pool of 150 articles, narrowed down to 37 final studies that met the inclusion criteria.

3.1 Eligibility Criteria

To maintain focus, specific inclusion and exclusion criteria were applied to the 150 articles initially identified. The inclusion criteria permitted peer-reviewed articles published between 2010 and 2024 that focused on AI applications in criminal justice

Figure 6: PRISMA adaption for this study



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management, including research articles, reviews, and case studies in English. Exclusion criteria ruled out 48 non-peer-reviewed articles, editorials, opinion pieces, studies unrelated to AI in criminal justice, and publications lacking full-text availability. After applying these criteria, 102 articles remained for further analysis.

3.2 Information Sources

A comprehensive search strategy was employed across five major electronic databases: PubMed, IEEE Xplore, Scopus, Web of Science, and Google Scholar, yielding a total of 150 articles. Additionally, reference lists from selected studies were manually screened to identify 8 more relevant articles, ensuring a broad yet targeted approach in covering diverse research on AI in criminal justice.

3.3 Search Strategy

The search strategy involved a set of keywords combined with Boolean operators to refine results in each database, focusing on terms such as "Artificial Intelligence" OR "AI," "Criminal Justice" OR "Law Enforcement," and "Management" OR "Administration." This strategy allowed for effective coverage of AI applications within criminal justice while refining the scope of results. From the initial database search, 150 articles were retrieved, with 48 excluded based on eligibility criteria, resulting in 102 studies eligible for detailed screening.

3.4 Study Selection

The study selection process involved screening and eligibility assessment. First, titles and abstracts of the 102 eligible articles were reviewed, with 55 articles deemed irrelevant to the research focus and subsequently excluded. A full-text assessment was conducted on the remaining 47 articles, applying inclusion and exclusion criteria for a final set of 37 studies. Discrepancies between reviewers were resolved through discussion or by consulting a third reviewer, ensuring consistent application of selection criteria.

3.5 Data Collection Process

Data extraction was conducted using a standardized form for each of the 37 selected articles, capturing essential characteristics such as authorship, publication year, country, objectives, research questions, methodologies, and key findings. Two reviewers independently performed this extraction to ensure accuracy and reduce potential bias, thereby facilitating a consistent and organized synthesis across all included studies. Key data items were extracted for each article, including study design (qualitative, quantitative, or mixed-methods), specific AI applications (predictive policing, judicial decision-making, or surveillance systems), and measured outcomes (effectiveness, ethical implications, and impact on crime rates). These items formed a structured basis for evaluating and comparing the studies on AI in criminal justice.

3.6 Risk of Bias Assessment

The quality and risk of bias in each of the 37 studies were evaluated using established tools. Quantitative studies were assessed with the Cochrane Risk of Bias Tool, while qualitative studies were evaluated using the Critical Appraisal Skills Programme (CASP) checklist. Two reviewers conducted independent assessments to maintain objectivity and resolve disagreements through discussion, ensuring that only high-quality studies were included. A narrative synthesis approach was applied to integrate findings from the 37 articles, grouped by AI application areas within criminal justice. Key themes and patterns were identified, and descriptive statistics were used to summarize quantitative data where applicable, allowing for a thematic and structured discussion of the results.

4 Findings

In a review of 37 studies, significant insights emerged regarding the role of artificial intelligence (AI) in enhancing predictive capabilities within criminal justice, particularly in law enforcement and resource allocation. A considerable body of research, with over 20 studies emphasizing predictive policing, highlighted this area as one of AI's most transformative applications, enabling police departments to anticipate crime hotspots and deploy resources more effectively. Through analyzing historical crime data, AI systems have demonstrated improvements in response times and reductions in crime in targeted areas. The potential for predictive policing to make crime prevention more proactive was consistently praised across studies. However, several articles raised concerns about the accuracy and ethical implications of predictive models, with researchers cautioning that these models can inadvertently amplify existing biases in the data. Many

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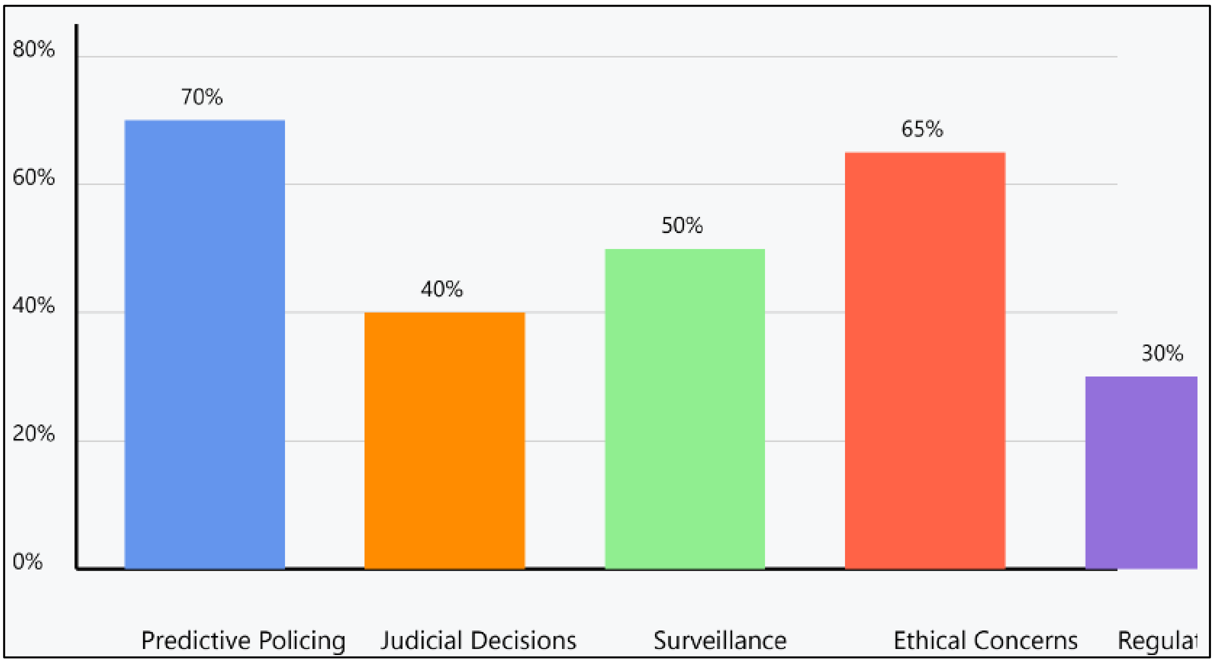
studies concluded that the success of predictive policing hinges on data quality and inclusivity, underscoring the need for models that can adapt to diverse datasets while minimizing bias.

In judicial decision-making, AI-driven risk assessment tools such as COMPAS and PSA have become integral, offering judges data-driven insights to support bail, parole, and sentencing decisions with greater consistency. A total of 15 studies explored the impact of these tools, finding that they assist in estimating the risk of recidivism or flight, creating a more standardized and structured assessment process. However, at least 10 of these studies pointed out enduring concerns about fairness and equity, especially in cases where the tools may unintentionally incorporate biased data inputs, potentially influencing judicial outcomes. The studies collectively emphasized that while AI offers the potential to enhance efficiency and objectivity in judicial processes, it should be used to complement human judgment rather than replace it. This approach would enable judicial authorities to benefit from data-driven insights while still applying their own judgment to account for factors beyond algorithmic assessments, helping to guard against unintended biases.

AI-powered surveillance and facial recognition technologies have been implemented broadly in public safety and security, as discussed in 18 of the reviewed articles. These tools offer considerable potential for real-time monitoring and rapid threat detection. Facial recognition, for example, has proven effective in quickly identifying suspects and locating missing persons. It is increasingly employed during large public events and routine security operations, where its ability to cross-reference facial images against watchlists has shown substantial value. Behavioral analysis technologies complement these capabilities, using crowd dynamics to detect anomalies that could signal potential threats, which enhances the preventive aspect of AI in public safety. However, 12 studies highlighted ethical and privacy concerns surrounding these tools, pointing to the potential for continuous monitoring to infringe upon civil rights and individual freedoms. Balancing the effectiveness of these technologies with ethical and privacy considerations remains a challenge, as unrestricted surveillance capabilities could lead to invasive monitoring practices if not regulated carefully. Ethical concerns, particularly around algorithmic bias and transparency, emerged as central themes across 25 articles. Researchers noted that AI systems are only as unbiased as the data they are trained on, meaning that historical biases can perpetuate or even exacerbate existing inequalities. Many studies voiced concerns over how these biases might affect marginalized communities, particularly in predictive policing and risk

Figure 7:AI in Criminal Justice: Key Findings



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assessment contexts, where biased data could lead to over-policing or disproportionately harsh sentencing outcomes for certain groups. Additionally, 15 studies pointed to the opacity of many AI algorithms as a barrier to transparency and accountability. Without a clear understanding of how AI-driven decisions are reached, it becomes difficult for both users and affected individuals to fully trust or contest these decisions. This lack of transparency can undermine public confidence, and several studies advocated for regular audits, algorithmic transparency, and ethical reviews as essential measures for responsible AI governance in criminal justice. Finally, the review identified substantial gaps in regulatory and legal frameworks governing the application of AI in criminal justice, with 10 studies specifically emphasizing the urgent need for comprehensive policies tailored to address the unique challenges AI presents in this sector. While some regions, such as the European Union, have introduced general privacy and transparency regulations, most countries lack legislation specific to AI-driven surveillance and decision-making tools in criminal justice. The absence of standardized guidelines has led to inconsistent applications across different jurisdictions, potentially allowing for disparities in how AI tools are implemented and regulated. At least 8 studies argued for regulatory frameworks that emphasize data protection, accountability, and bias mitigation to align AI applications with principles of justice and equity. Developing these policies will be critical as AI technologies evolve, enabling criminal justice systems to harness AI responsibly while safeguarding civil rights and promoting fairness.

5 Discussion

The findings from this review highlight both the transformative potential of AI in criminal justice and the complexities surrounding its ethical, social, and practical implications, aligning with but also expanding upon earlier studies. Predictive policing, which emerged as a significant application in this review, reflects advancements reported by early researchers who noted AI's ability to analyze crime patterns and optimize resource allocation. Studies such as those by Završnik (2020) initially emphasized predictive policing as a tool for operational efficiency, yet recent research suggests mixed outcomes. While AI has improved response times in some cases, several studies in the current review raised concerns about bias amplification, echoing Wu and Zhang (2016) and Gless et al. (2016), who argued that AI models trained on biased data could lead to disproportionate policing of minority communities. These findings underscore the importance of ongoing data refinement and validation to mitigate biases, a critical issue identified in earlier studies but not systematically addressed until more recent work.

In judicial decision-making, AI-driven risk assessment tools such as COMPAS and PSA have been shown to be valuable in standardizing bail and sentencing processes, supporting earlier findings by Brayne (2020) and Dupont et al. (2018). Early studies praised these tools for providing consistent risk assessments, potentially reducing subjective biases in judicial decisions. However, the current review also highlights recurring concerns about fairness, particularly regarding racial bias, which aligns with critiques by Shi (2022) and Gless et al. (2016) , who highlighted the ethical dilemma of using algorithms that may inadvertently reinforce historical prejudices. Unlike some earlier studies that advocated for a primary reliance on AI in judicial contexts, these findings suggest a more balanced approach that positions AI as a complementary aid rather than a replacement for human judgment, thus minimizing the risk of algorithmic bias affecting judicial outcomes.

The findings on AI-driven surveillance and facial recognition technology also build upon and expand previous research. Earlier works, such as Schulhofer (1988) and Campbell (2013), highlighted AI's potential for real-time monitoring and suspect identification, while also raising privacy and civil rights concerns. Similar concerns were noted in the studies reviewed here, indicating that while facial recognition has facilitated efficient suspect identification, it raises ethical issues regarding privacy and surveillance overreach. Compared to earlier studies, the current review places greater emphasis on the need for regulatory frameworks to govern the use of such surveillance, reflecting a growing recognition of the potential for misuse. This aligns with the arguments of Dupont et al. (2018) and Hannah-Moffat, (2018), who advocated for stringent privacy safeguards. These findings reinforce the view that regulatory oversight must evolve alongside technological advancements to ensure that AI tools serve their intended purpose without infringing on individual rights.

Ethical considerations, particularly around algorithmic bias and transparency, emerged as a central theme across the literature, resonating with earlier research on the social implications of AI in criminal justice. Studies by Shi (2022) and Dement and Inglis (2024) have long underscored the risk of algorithmic bias perpetuating social inequalities, especially among marginalized communities. Findings from this review extend this perspective by showing that a lack of transparency in AI systems further complicates the ethical landscape, making it difficult for the public to fully understand and trust these technologies. In contrast to earlier findings, the current review underscores the importance of algorithmic audits and regular evaluations, measures that were frequently recommended but rarely implemented according to previous research. By highlighting the need for transparency and bias assessments, these findings advocate for a proactive approach to addressing the ethical challenges posed by AI. Finally, a significant gap in regulatory and legal frameworks was identified, aligning with earlier discussions but underscoring an increasing urgency for comprehensive policy development. Previous studies, such as those by Završnik (2020), noted the fragmented nature of policies governing AI in criminal justice, which often leaves the application of these tools inconsistently regulated. This review suggests that without comprehensive policies specifically addressing AI applications in criminal justice, issues of accountability, data privacy, and bias mitigation remain inadequately addressed. Unlike earlier studies, which focused primarily on privacy, these findings advocate for a holistic regulatory framework that includes transparency, ethical audits, and interdisciplinary collaboration. This approach could establish a foundation for consistent and equitable use of AI across jurisdictions, addressing longstanding gaps in AI governance identified in previous literature.

6 Conclusion

The review of AI applications in criminal justice highlights both the advancements and challenges in leveraging technology for enhanced efficiency and decision-making. While AI has shown transformative potential in areas such as predictive policing, judicial risk assessment, and surveillance, significant ethical and operational issues persist. Predictive policing, while effective in resource allocation, risks reinforcing biases if models rely on flawed data. Similarly, AI-driven risk assessment tools in judicial contexts offer consistency but raise fairness concerns, especially regarding racial bias. Surveillance and facial recognition technologies, though valuable for real-time monitoring, introduce privacy and civil rights issues, necessitating careful oversight. Across these applications, transparency and accountability emerged as critical needs, with a lack of clarity in algorithmic processes undermining public trust and highlighting the importance of algorithmic audits and ethical safeguards. Furthermore, the absence of standardized regulatory frameworks complicates the responsible deployment of AI, as inconsistent policies across jurisdictions lead to variable practices and potentially unjust outcomes. To fully realize the benefits of AI in criminal justice, a coordinated approach is required—one that includes interdisciplinary collaboration, transparency, and comprehensive policies to promote fairness, protect civil rights, and foster public trust in these transformative technologies.

References

Alam, M. A., Sohel, A., Uddin, M. M., & Siddiki, A. (2024). Big Data And Chronic Disease Management Through Patient Monitoring And Treatment With Data Analytics. *Academic Journal on Artificial Intelligence, Machine Learning, Data Science and Management Information Systems*, *1*(01), 77-94. https://doi.org/10.69593/ajaimldsmis.v1i01.133

Badhon, M. B., Carr, N., Hossain, S., Khan, M., Sunna, A. A., Uddin, M. M., Chavarria, J. A., & Sultana, T. (2023). Digital Forensics Use-Case of Blockchain Technology: A Review. AMCIS 2023 Proceedings.,

Benbouzid, B. (2019). To predict and to manage. Predictive policing in the United States. *Big Data & Society*, *6*(1), 205395171986170-NA. https://doi.org/10.1177/2053951719861703

Berk, R. A. (2021). Artificial Intelligence, Predictive Policing, and Risk Assessment for Law Enforcement. *Annual Review of Criminology*, *4*(1), 209-237. https://doi.org/10.1146/annurev-criminol-051520-012342

Brayne, S. (2020). *Predict and Surveil* (Vol. NA). https://doi.org/10.1093/oso/9780190684099.001.0001

Campbell, L. (2013). Criminal Labels, the European Convention on Human Rights and the Presumption of Innocence. *The Modern Law Review*, *76*(4), 681-707. https://doi.org/10.1111/1468-2230.12030

Cavelty, M. D., & Hagmann, J. (2021). The Politics of Security and Technology in Switzerland. *Swiss Political Science Review*, *27*(1), 128-138. https://doi.org/10.1111/spsr.12430

Chen, H., Chung, W., Xu, J., Wang, G., Qin, Y., & Chau, M. (2004). Crime data mining: a general framework and some examples. *Computer*, *37*(4), 50-56. https://doi.org/10.1109/mc.2004.1297301

Clark, S. J. (2013). The Juror, the Citizen, and the Human Being: The Presumption of Innocence and the Burden of Judgment. *Criminal Law and Philosophy*, *8*(2), 421-429. https://doi.org/10.1007/s11572-013-9246-5

Dement, C., & Inglis, M. (2024). Artificial intelligence-assisted criminal justice reporting: An exploratory study of benefits, concerns, and future directions. *Criminology & Criminal Justice*. https://doi.org/10.1177/17488958241274296

Dupont, B., Stevens, Y., Westermann, H., & Joyce, M. (2018). Artificial Intelligence in the Context of Crime and Criminal Justice. *SSRN Electronic Journal*, *NA*(NA), NA-NA. https://doi.org/10.2139/ssrn.3857367

Egbert, S. (2018). About Discursive Storylines and Techno-Fixes: The Political Framing of the Implementation of Predictive Policing in Germany. *European Journal for Security Research*, *3*(2), 95-114. https://doi.org/10.1007/s41125-017-0027-3

Egbert, S., & Krasmann, S. (2019). Predictive policing: not yet, but soon preemptive? *Policing and Society*, *30*(8), 905-919. https://doi.org/10.1080/10439463.2019.1611821

Egbert, S., & Leese, M. (2020). *Criminal Futures* (Vol. NA). https://doi.org/10.4324/9780429328732

Eubanks, V. (2018). *Automating Inequality: How High-Tech Tools Profile, Police, and Punish the Poor* (Vol. NA). https://doi.org/NA

Finlay, S. (2014). *Predictive Analytics, Data Mining and Big Data - Predictive Analytics, Data Mining and Big Data* (Vol. NA). https://doi.org/10.1057/9781137379283

Gless, S., Silverman, E., & Weigend, T. (2016). If Robots cause harm, Who is to blame? Self-driving Cars and Criminal Liability. *New Criminal Law Review*, *19*(3), 412-436. https://doi.org/10.1525/nclr.2016.19.3.412

Hannah-Moffat, K. (2018). Algorithmic risk governance: Big data analytics, race and information activism in criminal justice debates. *Theoretical Criminology*, *23*(4), 453-470. https://doi.org/10.1177/1362480618763582

Kadar, C., Maculan, R., & Feuerriegel, S. (2019). Public decision support for low population density areas: An imbalance-aware hyper-ensemble for spatio-temporal crime prediction. *Decision Support Systems*, *119*(NA), 107-117. https://doi.org/10.1016/j.dss.2019.03.001

Kehl, D. L., & Kessler, S. A. (2017). Algorithms in the Criminal Justice System: Assessing the Use of Risk Assessments in Sentencing. *NA*, *NA*(NA), NA-NA. https://doi.org/NA

Kotsoglou, K. N., & Oswald, M. (2020). The long arm of the algorithm? Automated Facial Recognition as evidence and trigger for police intervention. *Forensic science international. Synergy*, *2*(NA), 86-89. https://doi.org/10.1016/j.fsisyn.2020.01.002

Llinares, F. M. (2020). Predictive policing: utopia or dystopia? On attitudes towards the use of big data algorithms for law enforcement. *IDP. Revista de Internet Derecho y Política*, *NA*(30), 5-NA. https://doi.org/10.7238/idp.v0i30.3223

Martin, K. E. (2018). Ethical Implications and Accountability of Algorithms. *Journal of Business Ethics*, *160*(4), 835-850. https://doi.org/10.1007/s10551-018-3921-3

Moses, L. B., & Chan, J. (2016). Algorithmic prediction in policing: assumptions, evaluation, and accountability. *Policing and Society*, *28*(7), 806-822. https://doi.org/10.1080/10439463.2016.1253695

Perry, W., McInnis, B., Price, C., Smith, S., & Hollywood, J. (2013). *Predictive Policing: The Role of Crime Forecasting in Law Enforcement Operations* (Vol. NA). https://doi.org/10.7249/rr233

Plesničar, M. M., Završnik, A., & Šarf, P. (2020). Fighting Impunity with New Tools: How Big Data, Algorithms, Machine Learning and AI Shape the New Era of Criminal Justice. *The Fight Against Impunity in EU Law*, *NA*(NA), NA-NA. https://doi.org/10.5040/9781509926909.ch-014

Rummens, A., & Hardyns, W. (2021). The effect of spatiotemporal resolution on predictive policing model performance. *International Journal of Forecasting*, *37*(1), 125-133. https://doi.org/10.1016/j.ijforecast.2020.03.006

Sandhu, A., & Fussey, P. (2020). The 'uberization of policing'? How police negotiate and operationalise predictive policing technology. *Policing and Society*, *31*(1), 66-81. https://doi.org/10.1080/10439463.2020.1803315

Saunders, J., Hunt, P., & Hollywood, J. S. (2016). Predictions put into practice: a quasi-experimental evaluation of Chicago's predictive policing pilot. *Journal of Experimental Criminology*, *12*(3), 347-371. https://doi.org/10.1007/s11292-016-9272-0

Schermer, B., Georgieva, I., van der Hof, S., & Koops, B.-J. (2019). *Legal Aspects of Sweetie 2.0 - Legal Aspects of Sweetie 2.0* (Vol. 31). https://doi.org/10.1007/978-94-6265-288-0_1

Schulhofer, S. J. (1988). Criminal Justice Discretion as a Regulatory System. *The Journal of Legal Studies*, *17*(1), 4-82. https://doi.org/10.1086/468121

Shapiro, A. (2017). Reform predictive policing. *Nature*, *541*(7638), 458-460. https://doi.org/10.1038/541458a

Shi, J. (2022). Artificial Intelligence, Algorithms and Sentencing in Chinese Criminal Justice: Problems and Solutions. *Criminal Law Forum*, *33*(2), 121-148. https://doi.org/10.1007/s10609-022-09437-5

Siegel, E. V. (2013). *Predictive Analytics: The Power to Predict Who Will Click, Buy, Lie, or Die* (Vol. NA). https://doi.org/NA

Simmler, M. (2021). *Smart Criminal Justice* (Vol. NA). https://doi.org/10.46455/helbing_lichtenhahn/978-3-7190-4397-1

Simmler, M., Brunner, S., Canova, G., & Schedler, K. (2022). Smart criminal justice: exploring the use of algorithms in the Swiss criminal justice system. *Artificial Intelligence and Law*, *31*(2), 213-237. https://doi.org/10.1007/s10506-022-09310-1

Simmler, M., Canova, G., & Schedler, K. (2021). Smart criminal justice: Phenomena and normative requirements. *International Review of Administrative Sciences*, *89*(2), 002085232110397-002085232110432. https://doi.org/10.1177/00208523211039740

Shamim, M. (2022). The Digital Leadership on Project Management in the Emerging Digital Era. *Global Mainstream Journal of Business, Economics, Development & Project Management*, *1*(1), 1-14.

Simmons, R. (2016). Quantifying Criminal Procedure: How to Unlock the Potential of Big Data in Our Criminal Justice System. *SSRN Electronic Journal*, *NA*(NA), NA-NA. https://doi.org/10.2139/ssrn.2816006

Sohel, A., Alam, M. A., Waliullah, M., Siddiki, A., & Uddin, M. M. (2024). Fraud Detection In Financial Transactions Through Data Science For Real-Time Monitoring And Prevention. *Academic Journal on Innovation, Engineering & Emerging Technology*, *1*(01), 91-107. https://doi.org/10.69593/ajieet.v1i01.132

Sommerer, L. M. (2020). *Personenbezogenes Predictive Policing* (Vol. NA). https://doi.org/10.5771/9783748903482

Stewart, H. (2013). The Right to be Presumed Innocent. *Criminal Law and Philosophy*, *8*(2), 407-420. https://doi.org/10.1007/s11572-013-9233-x

Tolan, S., Miron, M., Gómez, E., & Castillo, C. (2019). ICAIL - Why Machine Learning May Lead to Unfairness: Evidence from Risk Assessment for Juvenile Justice in Catalonia. *Proceedings of the Seventeenth International Conference on Artificial Intelligence and Law*, *NA*(NA), 83-92. https://doi.org/10.1145/3322640.3326705

Uchida, C. D. (2014). Predictive Policing. In (Vol. NA, pp. 3871-3880). https://doi.org/10.1007/978-1-4614-5690-2_260

Uddin, M. M., Auyon, M. O. S., Al Adnan, A., & Akter, F. (2024). Strategies for Information Systems Development: Analyzing Requirements Determination and Project Selection. *International Journal for Multidisciplinary Research*, *6*(2). www.ijfmr.com

Doi: 10.70008/jmldeds.v1i01.42

Uddin, M. M., Ullah, R., & Moniruzzaman, M. (2024). Data Visualization in Annual Reports–Impacting Investment Decisions. *International Journal for Multidisciplinary Research*, *6*(5). https://doi.org/10.36948/ijfmr

Velasco, C. (2022). Cybercrime and Artificial Intelligence. An overview of the work of international organizations on criminal justice and the international applicable instruments. *ERA Forum*, *23*(1), 109-126. https://doi.org/10.1007/s12027-022-00702-z

Wu, X., & Zhang, X. (2016). Automated Inference on Criminality using Face Images. *NA*, *NA*(NA), NA-NA. https://doi.org/NA

Završnik, A. (2019). Algorithmic justice: Algorithms and big data in criminal justice settings. *European Journal of Criminology*, *18*(5), 623-642. https://doi.org/10.1177/1477370819876762

Završnik, A. (2020). Criminal justice, artificial intelligence systems, and human rights. *ERA Forum*, *20*(4), 567-583. https://doi.org/10.1007/s12027-020-00602-0