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Artificial Intelligence, Machine Learning, and Language Learning Models in Criminology: A Bibliometric Analysis

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Abstract
The use of bibliometric analysis to identify prominent research trends, influential authors, citation patterns, and thematic developments in the field of criminology is not given adequate attention in the body of literature. The paper employs a bibliometric analysis to examine AI, ML, and language learning models in criminology. Drawing on data from peer-reviewed literature, the study maps co-occurring concepts and assesses the intellectual structure of AI-criminology research. A dataset consisting of 143 publications was created by limiting the search to the "article" type and the subject categories "criminology" and "penology" in the Web of Science (WoS) database, using keywords such as "artificial intelligence," "ChatGPT," "machine learning," "AI," "generative AI," "natural language processing," and "criminology." Findings revealed a marked increase in publication output since 2019, with significant thematic focus on machine learning, predictive policing, cybercrime, and risk assessment. The field is characterized by moderate international collaboration, regional publication dominance, and a growing interest in applied technological solutions to crime. While established bibliometric laws like Lotka's and Bradford's only partially apply, the field demonstrates signs of rapid maturation and interdisciplinary convergence. The study concludes that advancing AI-criminology research requires stronger global cooperation, theoretical grounding, and regulatory frameworks to ensure responsible and equitable use of AI in the criminal justice system. These insights offer a foundational

understanding for scholars, policymakers, and practitioners aiming to navigate and shape the future of AI in criminological research and practice.

Keywords: Artificial intelligence, machine learning, language learning, models, criminology, bibliometric analysis

Introduction

Artificial Intelligence (AI) has rapidly gained prominence across various domains since its conceptual introduction by John McCarthy in 1956. McCarthy, a mathematician and logician, spearheaded the Dartmouth Summer Research Project on Artificial Intelligence, laying the foundation for a discipline focused on the development of "thinking machines." AI is broadly defined as the use of science and engineering to create systems that imitate human intelligence (McCarthy, 2004). Russell and Norvig (2016) further describe AI as the study of computer systems designed to model and simulate human cognitive functions. While current AI systems cannot fully replicate the wide spectrum of human tasks, they can match or surpass human performance in specific areas, such as problem-solving, language interpretation, and perception (Nilsson, 1998).

The evolution of AI has encompassed several distinct phases. Early research focused on symbolic logic-based approaches, where systems attempted to solve problems using logical rules (Newell & Simon, 1972). This era saw the development of programs that played games and solved mathematical problems. As the field matured, the emergence of machine learning (ML) marked a pivotal shift, introducing computational models capable of learning from data (Mitchell, 1997). Key innovations such as artificial neural networks (ANN) and genetic algorithms allowed computers to mimic human learning processes, further expanding the capabilities of AI (Rumelhart & McClelland, 1986; Goldberg, 1989).

Artificial neural networks are rooted in the mathematical modeling of the human brain, simulating the function of neurons to enable computers to learn from input data. ANN, as a subset of AI, underpins many learning systems by providing machines with the ability to learn through experience, much like humans do. This neural-inspired approach has produced remarkable results in tasks such as recognition, prediction, and classification (LeCun et al., 1989). Machine learning, more broadly, enables systems to improve their performance autonomously by analyzing vast datasets, constructing models to recognize patterns, and validating these models against new data to ensure effectiveness (Brink et al., 2016).

The application of AI and ML extends beyond technical fields to areas such as criminology, where data-driven approaches are increasingly vital. Criminological research, including crime causation analysis, offender profiling, and predictive modeling, has become more systematic through the integration of AI technologies. These advancements enhance the effectiveness of crime prevention and support informed decision-making in criminal justice systems. However, prior studies (Van Raan, 2014; Zupic & Čater, 2015) have largely overlooked this intersection. To address this gap, the present study employs bibliometric analysis to examine the integration of AI, ML, and language learning models within criminology, mapping the evolving academic landscape and evidencing the transformative impact of digital technologies on the field.

Objectives of the Study

1. To examine AI, ML, and language learning models within the field of criminology, using a bibliometric analysis.
2. To map key trends, identify influential authors and citation networks, explore co-occurring concepts, and uncover emerging paradigms that define this growing interdisciplinary area.

3. To provide a comprehensive overview of how AI-driven technologies are shaping criminological inquiry, highlight existing research gaps, and offer insights for future scholarly and policy-oriented engagement in the domain.

Literature and Empirical Review

Raffaele Garofalo was the first to use the term "criminology." However, it is known that Cesare Lombroso (1835-1909), an Italian criminologist and physician, is the father of modern criminology (Newburn, 2017). Criminology is regarded as a scientific discipline that seeks to explain crime and criminal behaviour. Its focus encompasses crime and its forms, the causes of crime, criminal typologies, and deviance, employing scientific data and methodologies to develop theories. Through its body of knowledge and practices, criminology contributes to solving the problem of crime (Hagan & Daigle, 2020). This makes criminology a science that directly impacts individuals and society.

Different approaches exist in defining criminology, shaped primarily by the priorities of the academic disciplines addressing it. Despite these variations, it is commonly defined as the science that studies crime, criminals, and criminal justice (Carrabine et al., 2020). Another definition by Lubago (2021) is that criminology is the study of crime, attempts to control it, and societal attitudes toward it. It can be argued that the existence of crime is a consequence of human existence itself. This phenomenon, emerging alongside humanity in various dimensions and interpretations, laid the groundwork for the development of criminology. The scientific examination of the criminal who commits the offense, the act itself, and the affected victim has led to the emergence of criminology as a discipline (Sokullu-Akıncı, 2020). Criminology is the scientific study of crime, criminals, and possible ways of curbing crime (Okorie, 2023). It implies that an expert in criminology is called a criminologist.

Bibliometrics involves the systematic analysis of academic literature using data extracted from indexed databases. This method examined publications, citation patterns, and contributions by authors, institutions, and countries to provide a comprehensive overview of a scientific field's structure, dynamics, and performance. Through bibliometric techniques, researchers can identify influential works, assess scientific productivity, and track the evolution of research topics over time (Zupic & Čater, 2015). A key advantage of bibliometrics is its ability to measure scientific impact via citation analysis, reveal trends in knowledge growth, and enable evidence-based evaluation of research performance.

One prominent application of bibliometrics is science mapping, which generates visual diagrams to illustrate how different segments of a field are interconnected, such as collaborative networks among authors, co-occurrence of keywords, and institutional partnerships (Van Raan, 2014). By offering a macro-level perspective, science mapping uncovers thematic clusters, emerging research fronts, and interdisciplinary linkages that might remain obscured in traditional literature reviews.

Empirical Review

Berk and Bleich (2014) examined the challenges in sentencing risk forecasts where ML is not feasible due to limited infrastructure. They proposed enhanced classification trees as a practical alternative, demonstrating that modest-sized trees built from large datasets can provide reliable, interpretable forecasts. Their method systematically managed ambiguous cases, offering a viable substitute to ML in resource-constrained environments. Chan and Bennett-Moses (2016) examined how big data and ML revolutionize criminology. They argued that although Big Data introduces novel tools and insights, its purported fundamental shift is such as prioritizing correlation over

causation.

Berk (2017) evaluated the use of ML forecasts in parole decisions. Quasi-experimental results showed that ML forecasts contributed to reductions in both violent and nonviolent re-arrests, suggesting risk assessments improve parole decisions when offense type is considered. Hayward et al. (2021) introduced AI concepts in criminology, categorizing AI-related crime as crimes aided by AI, crimes targeting AI systems, and crimes committed by AI itself. They emphasized AI's dual role in amplifying traditional crimes and enabling new digital offenses while transforming policing and criminal justice through predictive and preventive technologies.

Wheeler and Steenbeek (2021) demonstrated that the Random Forest ML algorithm produces highly accurate long-term crime forecasts at micro-geographic scales, outperforming other methods such as Risk Terrain Models. They highlighted advances in interpreting random forests, revealing spatially varying, nonlinear crime predictors, and combining strong predictive accuracy with enhanced transparency. Mikhailov and Kokodey (2023) examined the rapid rise of AI in creative domains alongside its criminal misuse, such as deepfakes, cyberbullying, and military applications. They reviewed international regulatory efforts and proposed preventive measures, including user verification, AI content labeling, legal reforms, and bans on autonomous weapons, to mitigate AI's criminal risks.

Wang et al. (2023) investigated interpretable ML models for recidivism prediction, comparing them with black-box models and existing tools like COMPAS across multiple jurisdictions. Their interpretable models achieve comparable accuracy, improved fairness, and practical usability, especially when trained regionally. The study supported interpretable ML as a fair, effective alternative for justice system risk assessments.

Methods and Materials

This study employed a qualitative research design anchored in document analysis, systematically examining both written and oral sources within criminology and penology through artificial intelligence (AI)-based methodologies. A dataset comprising 143 academic articles indexed in the Web of Science (WoS) database was curated, leveraging WoS's comprehensive international scope and peer-reviewed content to ensure analytical reliability and validity (Clarivate, 2023). The Bibliometrix package in the R programming environment was utilised for its robust visualisation and analytical features, particularly in generating science maps, co-authorship networks, and keyword analyses. Data collection was facilitated by Karamanoğlu Mehmetbey University's institutional access, using advanced WoS search tools for precise retrieval, and records were exported in BibTeX format to support rigorous cross-validation of findings.

The dataset was constructed using targeted search parameters: keywords including "artificial intelligence", "CHATGPT", "machine learning", "AI", "generative AI", and "natural language processing", combined with criminological terms such as "criminology" or "criminology*." Filters limited results to articles within the subject area of criminology or penology, with the search and download completed on 26 May 2025. The Bibliometrix package, accessed via the Biblioshiny interface in RStudio, facilitated bibliometric analysis and data visualisation (Aria & Cuccurullo, 2017). Only peer-reviewed research articles referencing AI or related technologies in their titles, abstracts, or keywords and classified within criminology or penology were included, while non-research articles, books, proceedings, and studies lacking explicit AI relevance were excluded, thereby ensuring a focused and high-quality dataset.

Results

Figure 1. Main Information

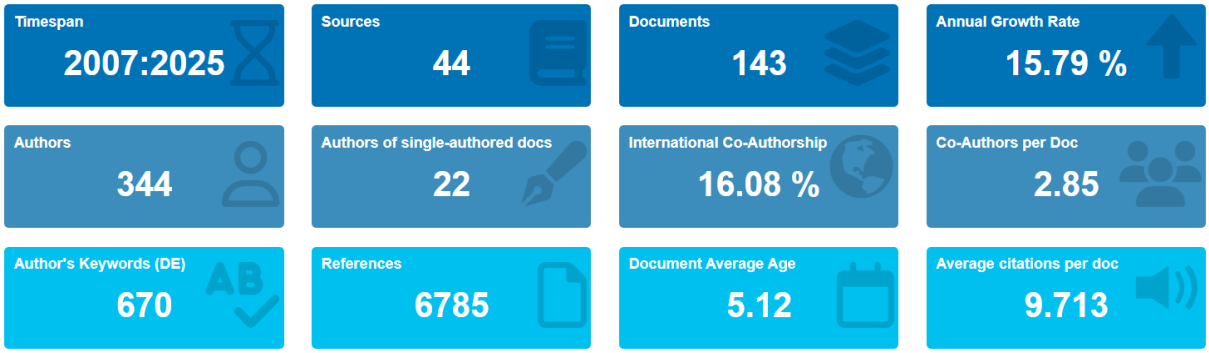
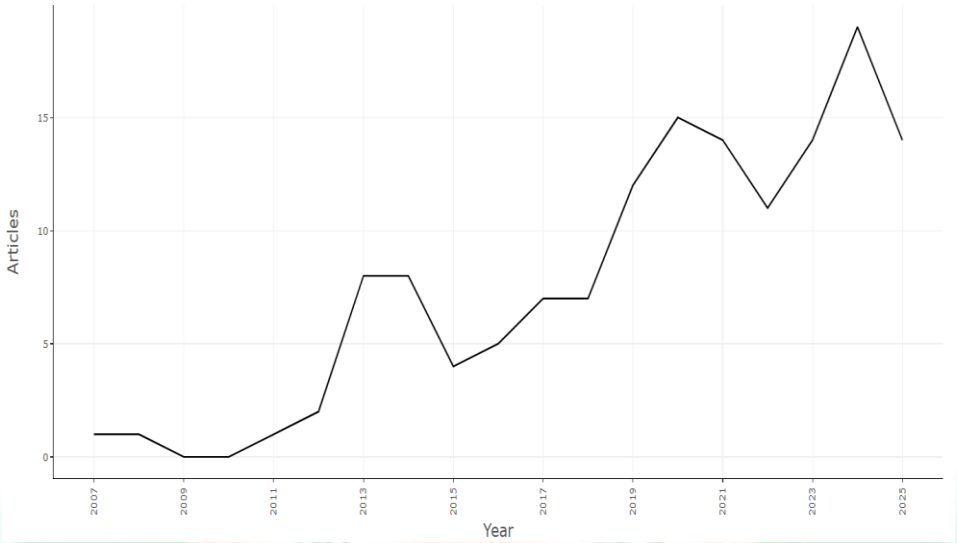


Figure 1 presents essential bibliometric indicators demonstrating research dynamics at the intersection of artificial intelligence (AI), machine learning, language models, and criminology from 2007 to 2025. The analysis encompasses 344 authors and 670 keywords, with an average of 2.85 co-authors per document and a 16.08% international co-authorship rate, reflecting moderate but increasing global collaboration. The presence of 22 single-author publications highlights ongoing individual scholarship. The field displays robust growth, with an annual publication increase of 15.79% and an average of 9.713 citations per document, suggesting a strong academic influence and rapid development. Cumulatively, 6,785 referenced works underpin this literature, indicating that AI–criminology research is highly interdisciplinary, with recent years marking its transition from an emerging to a firmly established domain (Aria & Cuccurullo, 2017). Figure 2 illustrates the annual escalation in the number of publications at the intersection of AI and criminology research.

Figure 2. Annual Scientific Publications

Year	Number of Articles
2007	1
2008	1
2009	0
2010	0
2011	1
2012	2
2013	8
2014	8
2015	4
2016	5
2017	7
2018	7
2019	12
2020	15
2021	14
2022	11
2023	14
2024	19
2025	14



Publication trends from 2007 to 2025 reveal three distinct phases. In the early period (2007–2012), research output was minimal, with zero to two articles per year and no publications in 2009 or 2010, indicating limited activity or data collection challenges. The middle phase (2013–2018) saw an abrupt rise, with eight articles in 2013 and annual output stabilising at four to eight publications, signalling increased and sustained research efforts. From 2019 to 2024, the field experienced rapid expansion, peaking at 15 articles in 2020 and 19 in 2024, growth likely driven by the COVID-19 pandemic, enhanced institutional backing, and greater international engagement. Of the 143 articles published over 19 years (average 7.5 per year), 95 articles (66%) appeared between 2019 and 2025, highlighting recent acceleration (Clarivate, 2023).

Descriptive Findings

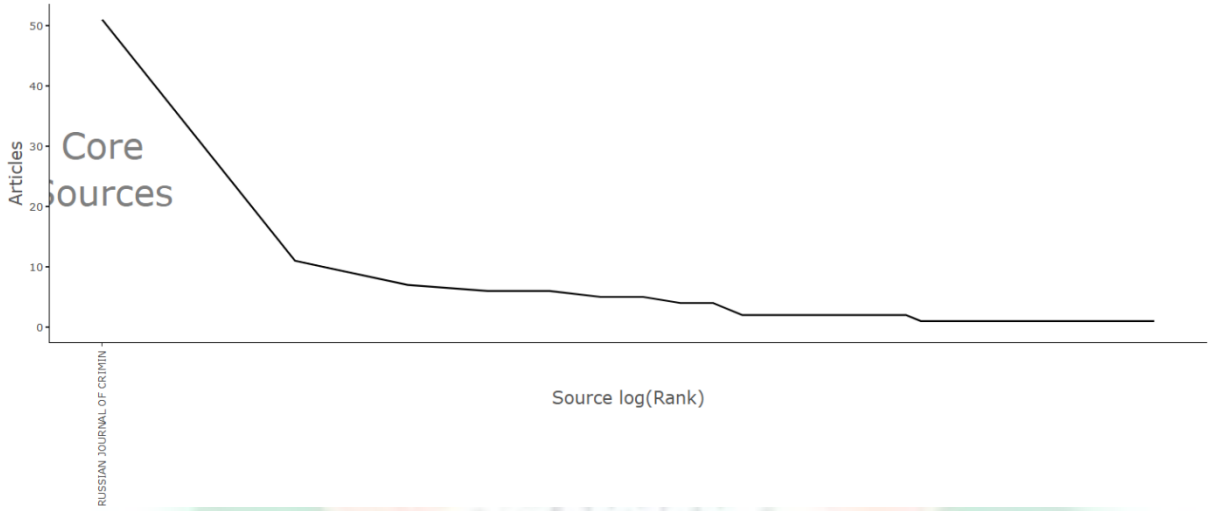
Figure 3 shows key bibliometric indicators relating to research on AI, ML and language models in criminology, as determined by Bradford's law.

Figure 3. Core Sources by Bradford's Law

SO	Rank	Freq	cumFreq	Zone
Russian Journal of Criminology	1	51	51	Zone 1
Journal of Quantitative Criminology	2	11	62	Zone 2
International Journal of Offender Therapy and Comparative Criminology	3	7	69	Zone 2
Criminology & Public Policy	4	6	75	Zone 2
Journal of Experimental Criminology	5	6	81	Zone 2
Asian Journal of Criminology	6	5	86	Zone 2
International Journal of Cyber Criminology	7	5	91	Zone 2
British Journal Of Criminology	8	4	95	Zone 2
Criminology & Criminal Justice	9	4	99	Zone 2
Crime Science	10	2	101	Zone 3

**SO (Source Outlet): The name of the journal. Rank: Position based on frequency (Freq). Freq: Number of citations/publications. cumFreq: Cumulative frequency (running total). Zone:*

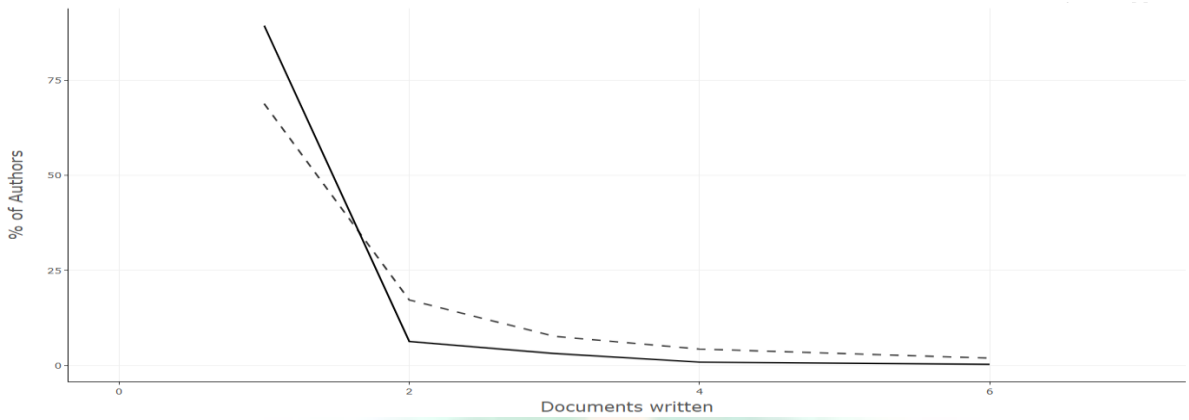
Categorization based on Bradford's Law (Zone 1=core, Zone 2=moderate, Zone 3=low-frequency sources).



The citation analysis encompassed 101 citations from 10 journals, structured into three zones according to Bradford's Law. Zone 1 is dominated solely by the Russian Journal of Criminology with 51 units (50.5%), indicating its centrality and primary influence. Zone 2 includes eight journals contributing 48 units (47.5%), each providing between four and eleven citations, reflecting a moderate yet balanced influence and diversity of sources. Zone 3 consists only of Crime Science with two units (2%), suggesting limited impact, possibly due to its niche or recent emergence. While Bradford's Law predicts a 1:n:n² distribution, the observed diversity in Zone 2 contrasts with Zone 3's minimal representation. Figure 4 also applies Lotka's Law to showcase key bibliometric indicators in AI and criminology research (Aria & Cuccurullo, 2017).

Figure 4. Author Productivity through Lotka's Law

Documents written	N. of Authors	Proportion of Authors	Theoretical
1	313	0,894	0,689
2	22	0,063	0,172
3	11	0,031	0,077
4	3	0,009	0,043
6	1	0,003	0,019



The analysis shows that most authors in the examined literature contributed only one article, with 313 out of 350 authors (89.4%) publishing a single work—much higher than the 60% predicted by Lotka's Law. As publication count increases, the number of contributing authors sharply declines; just 6.3% authored two articles, and only one author (0.3%) published six. While authors with three or more articles are generally deemed 'productive,' they represent only 4.3% of the total, highlighting the rarity of high productivity in this field. Lotka's Law, a core bibliometric principle, anticipates that few researchers produce most publications, following a $1/n^2$ relationship. However, this dataset reveals a greater concentration of one-time contributors and fewer prolific authors than the law predicts, suggesting a field characterized by widespread but less concentrated research activity.

Table 1. Authors' Local Impact

Author	h-index	g-index	m-index	TC	NP	PY start
Begishev, I. R.	3	3	0.375	47	3	2018
Berk, R	3	3	0.25	169	3	2014
Lee, S.	3	3	0.273	95	3	2015
Adeniran, A. I.	2	2	0.111	41	2	2008
Alonso, A. I.	2	3	0.4	27	3	2021
Bleich, J.	2	2	0.154	153	2	2013
Hipp, J. R.	2	2	0.5	66	2	2022
Khisamova, Z. I.	2	2	0.25	26	2	2018
Kim, J. H.	2	2	0.5	66	2	2022
Kirchebner, J.	2	3	0.667	11	3	2023

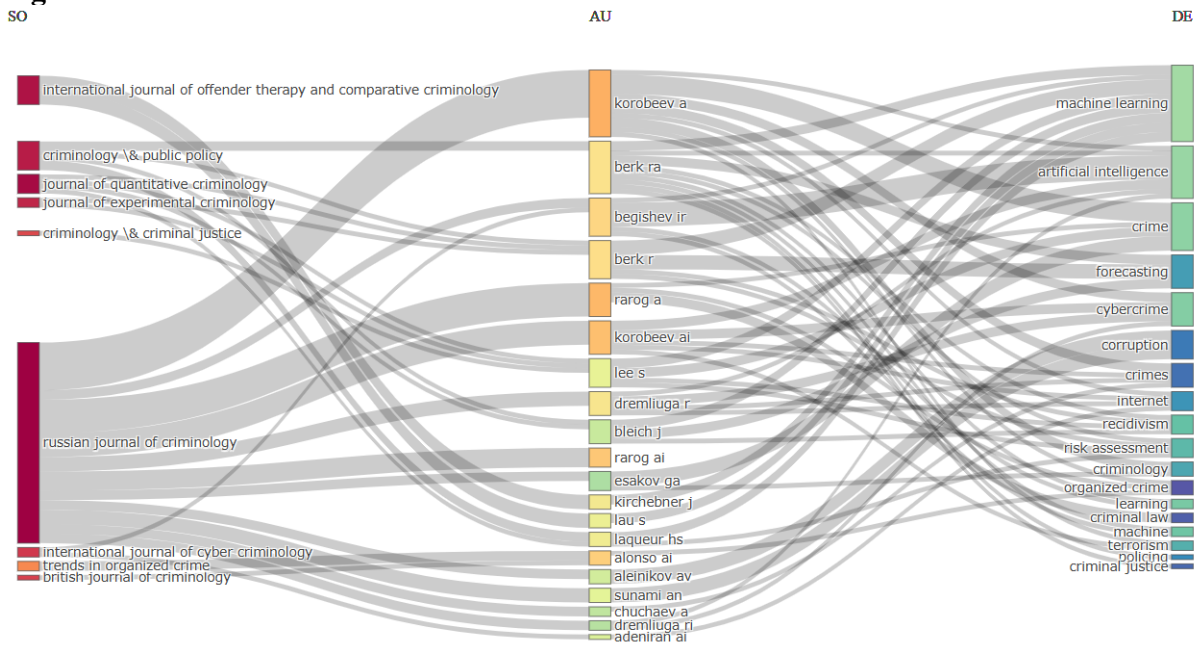
**TC: Total citations, NP: Number of publications, PY: Publish year*

Table 1 assesses the local academic influence of the top ten authors in AI, machine learning, and language models within criminology, using the h-index as a benchmark. The analysis reveals a dichotomy between productivity and influence: authors such as Berk (h-index = 3, TC = 169, NP = 3) and Bleich (h-index = 2, TC = 153, NP = 2) achieve high citation impact with limited output, indicating seminal status, while others like Begishev and Lee maintain moderate citation counts (TC = 47 and 95) with similar h-indices. This suggests that a few key works can disproportionately shape the field (Aria & Cuccurullo, 2017).

Career-stage differences are evident through m-index values, with early-career researchers such as Kirchebner (m = 0.667, PY Start = 2023) and Hipp/Kim (m = 0.5, PY Start = 2022) showing rapid

early impact, contrasting with established figures like Adeniran (m = 0.111, PY Start = 2008). The data highlight a technology-driven research focus, exemplified by high TC/NP ratios (e.g., Bleich's CPP = 76.5). However, small sample size (NP ≤ 3 for 80% of authors) and regional variations suggest caution in generalisation. Figure 5's Three-Field Plot visualises the top 20 authors, sources, and keywords, illustrating the interconnected landscape of this emerging field.

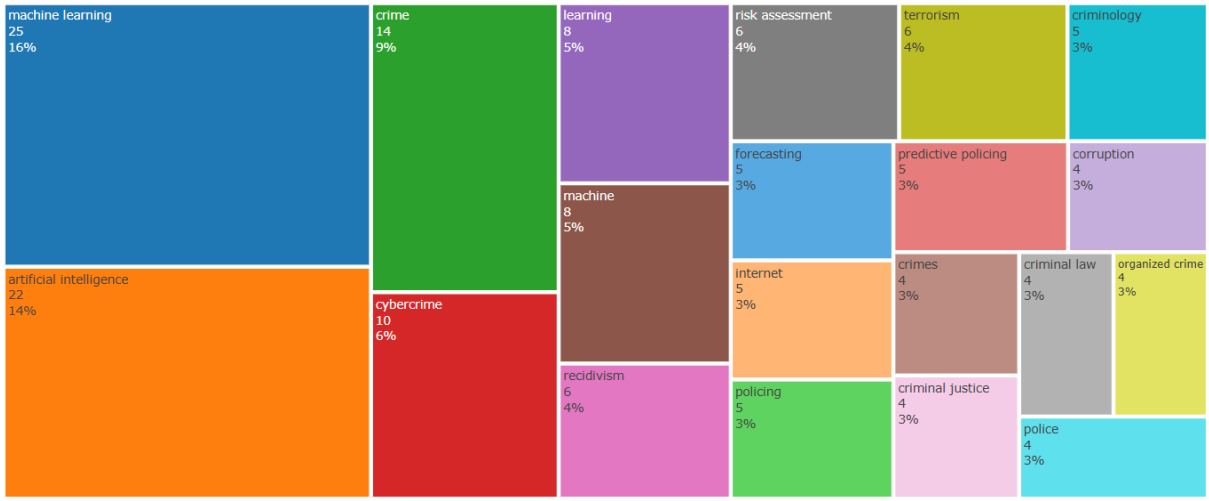
Figure 5. Three-Field Plot



The Three-Field Plot analysis delineates the structural distribution and research trends at the intersection of criminology, artificial intelligence (AI), and machine learning (ML). The central field, "Authors," presents the top 20 most prolific contributors, highlighting influential researchers and collaborative networks. The frequent recurrence of specific names suggests these scholars play pivotal roles in advancing interdisciplinary studies or shaping the domain's intellectual landscape (Aria & Cuccurullo, 2017). The left field, "Sources," lists the 20 most cited journals, with titles such as the International Journal of Offender Therapy and the Russian Journal of Commodity, illustrating preferred publication venues where criminology and technology intersect. The right field, "Keywords," features the 20 most common research terms, reflecting subdomains such as "cybercrime," "forecasting," and "corruption," that represent focal points for AI/ML applications within criminology.

Figure 6 displays a TreeMap visualisation based on authors' keywords, transparently illustrating the top 20 terms without synonym grouping or filtering. The size and colour intensity of each keyword are proportional to its frequency, providing an immediate visual cue to the prominence of specific themes. This unfiltered approach faithfully represents the terminological diversity and conceptual landscape, revealing dominant topics and the nuanced structure of contemporary research at the intersection of AI and criminology.

Figure 6. Tree Map



The TreeMap visualisation identifies the 20 most frequent keywords, elucidating predominant themes at the nexus of AI and criminology. The largest segments, "Machine Learning" (25 occurrences, 16%) and "Artificial Intelligence" (22 occurrences, 14%), highlight the technology-oriented trajectory of the field. These terms are closely linked to practical applications, notably predictive policing and risk assessment, indicating the integration of AI/ML into criminological practice (Aria & Cuccurullo, 2017). "Cybercrime" (10 occurrences, 6%) further signifies AI's role in addressing digital threats, while keywords like "crime," "terrorism," and "criminal law" show the merging of traditional and technological domains.

Lower-frequency keywords such as "corruption" and "military" suggest emerging but as yet underexplored areas, including AI-driven anti-corruption and defense research. Terms like "victim" and "police" reflect growing interest in victim-centred approaches and law enforcement's technological adoption. As shown in Table 2, the analysis spans 2007 to 2025, focusing on "Author's Keywords" without text preprocessing. Only terms appearing at least five times were included, with a maximum of three keywords per year. The final table presents the top 10 keyword entries, reflecting authentic research trends.

Table 2. Trend Topics

Term	Frequency	Year (Q1)	Year (Median)	Year (Q3)
Forecasting	5	2014	2017	2020
Internet	5	2019	2019	2021
Predictive Policing	5	2019	2019	2021
Crime	14	2013	2020	2024
Recidivism	6	2016	2020	2023
Risk Assessment	6	2019	2020	2023
Machine Learning	25	2019	2021	2024
Criminology	5	2014	2021	2021
Artificial Intelligence	22	2019	2022	2023
Cybercrime	10	2020	2022	2022

**Frequency: Number of occurrences. Year (Q1): First quartile (earlier trends). Year (Median): Median year (central trend). Year (Q3): Third quartile (recent trends).*

Analysis of key concepts, considering both frequency and temporal trends, demonstrates the increasing adoption of technology-based approaches within criminal justice and criminology. The

most frequent terms, "machine learning" (25 occurrences) and "artificial intelligence" (22 occurrences), underscore the integration of these technologies, with their prevalence particularly notable after 2019. Foundational terms such as "crime" (14) and "cybercrime" (10) also feature prominently, though their distribution varies. The median year for "cybercrime" and "AI" is 2022, indicating accelerated recent growth, while the first quartile (Q1) year for "predictive policing" and "risk assessment" is 2019, reflecting increased adoption of data-driven policing amid the pandemic (Aria & Cuccurullo, 2017).

Early adoption trends are evident for terms like "forecasting" (median year: 2017), associated initially with traditional statistical methods. While "criminology" shows a median year of 2021, "crime"—present from 2013—peaks in 2020, signalling evolving interpretations as digital technologies reshape the field. The 2019–2021 period emerges as pivotal, with "internet" and "predictive policing" clustering in both Q1 and median years, highlighting the pandemic's influence in accelerating digital transitions. High-frequency, recent terms confirm active research frontiers, whereas lower-frequency terms with recent median years, such as "cybercrime" and "risk assessment", suggest emerging niches or evolving ethical and methodological challenges. Table 3 examines the academic impact of the top 10 locally cited documents on AI, ML, and language models in criminology.

Table 3. Most Locally Cited Documents

Authors & Year	Journal	Local Citations	Global Citations	LC/GC Ratio (%)	Normalized Local Citations	Normalized Global Citations
Berk & Bleich (2014)	Journal of Quantitative Criminology	5	33	15.15	8,00	5,87
Berk, (2017)	Journal of Experimental Criminology	5	83	6.02	7,00	6,32
Chan & Bennett-Moses (2016)	Theoretical Criminology	3	95	3.16	5,00	4,48
Hipp, Lee, Ki, & Kim (2021)	Journal of Quantitative Criminology	3	58	5.17	11,00	8,39
Wang, Han, Patel & Rudin (2023)	Journal of Quantitative Criminology	2	47	4.26	7,00	6,85
Begishev & Khisamova (2018)	All-Russian Criminology Journal	1	14	7.14	7,00	1,21
Hayward & Maas (2021)	Crime, Media, Culture	1	31	3.23	7,00	1,44
Wheeler & Steenbeek	Journal of Quantitative	1	61	1.64	7,00	2,83

(2021)	Criminology					
Mikhailov & Kokodey (2023)	All-Russian Criminology Journal	1	1	100.00	3,50	0,15
Suzuki, Shimada, & Yamamoto (2023)	Asian Journal of Criminology	1	1	100.00	3,50	0,15

The analysis uncovers distinct patterns in scholarly impact when comparing global and local citation metrics. Highly cited works such as Berk (2017) and Chan & Bennett-Moses (2016), with 83 and 95 global citations (GC) respectively, demonstrate significant international influence. However, their local citation (LC) ratios (6.02% and 3.16%) are relatively low, suggesting these studies are more prominent globally than within local academic discourse. Conversely, studies in local journals, such as Mikhailov & Kokodey (2023) and Suzuki et al. (2023), achieve LC/GC ratios of 100%, yet their absolute citation counts remain minimal, reflecting niche relevance but limited global recognition (Aria & Cuccurullo, 2017).

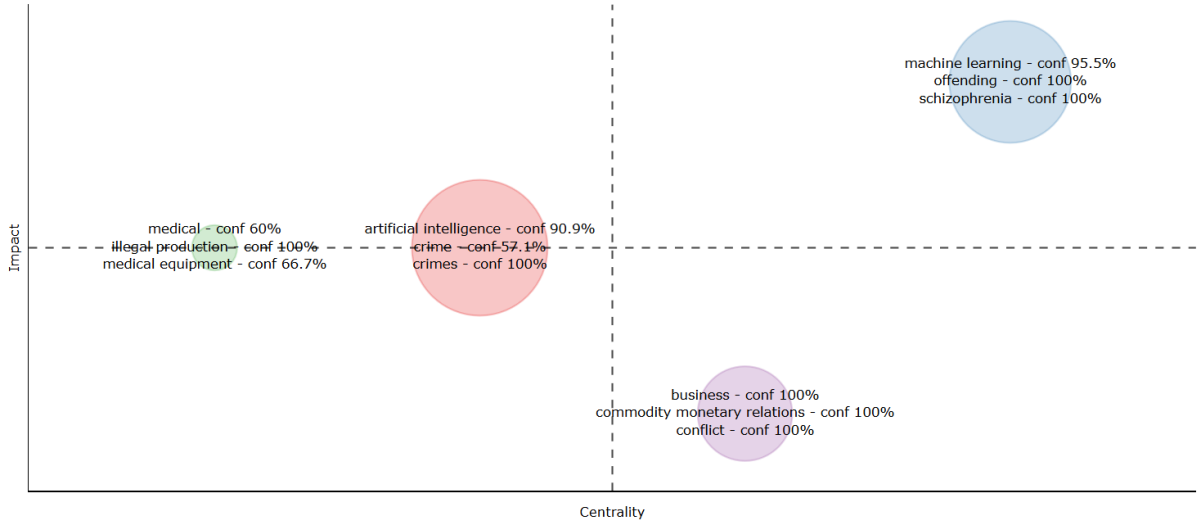
Journals like the Journal of Quantitative Criminology play a pivotal role, with examples such as Hipp et al. (2021) and Berk & Bleich (2014) showing robust local and global citation counts, underscoring their interdisciplinary significance. Regional journals, including the All-Russian Criminology Journal and Asian Journal of Criminology, contribute valuable insights to local contexts but often lack broader international visibility. Normalised citation metrics (adjusted for publication age) further highlight nuanced trends, as seen in Hipp et al. (2021), which leads with 11.0 normalised local citations, indicating swift local adoption.

A clear disparity is evident: globally influential research, such as Chan & Bennett-Moses (2016), often garners minimal local citations, while locally focused works remain regionally confined. This divergence may reflect differing research priorities in local versus global criminology agendas. Recent publications (2021–2023) by authors like Hipp et al. and Wang et al. demonstrate high normalised citation rates in both contexts, suggesting growing engagement with AI in criminology. Enhancing the international visibility of regional research could bridge critical gaps, with journals like the Journal of Quantitative Criminology serving as key platforms for interdisciplinary integration and field advancement.

Conceptual Findings

Figure 7 contains an analysis of 250 authors in the research field, and "Authors" has been selected as the unit of analysis. The relationship between authors was measured using the 'coupling' method based on "Author's Keywords." This approach aims to identify thematic similarities between authors who share common keywords. In the analysis, the academic impact of authors was evaluated using the "Local Citation Score," and clusters were also considered based on this impact measure. Each cluster was labeled using the keywords within the cluster ("Authors' keywords"), and each cluster contained a maximum of three labels. The size of the tags was set to 0.3. The Walktrap algorithm was used for clustering; this algorithm is effective in community detection and reveals the thematic groups formed by authors. Additionally, the minimum cluster frequency was set to 5, and the community repulsion value was set to "0"; this is a parameter aimed at optimizing the distinction between clusters.

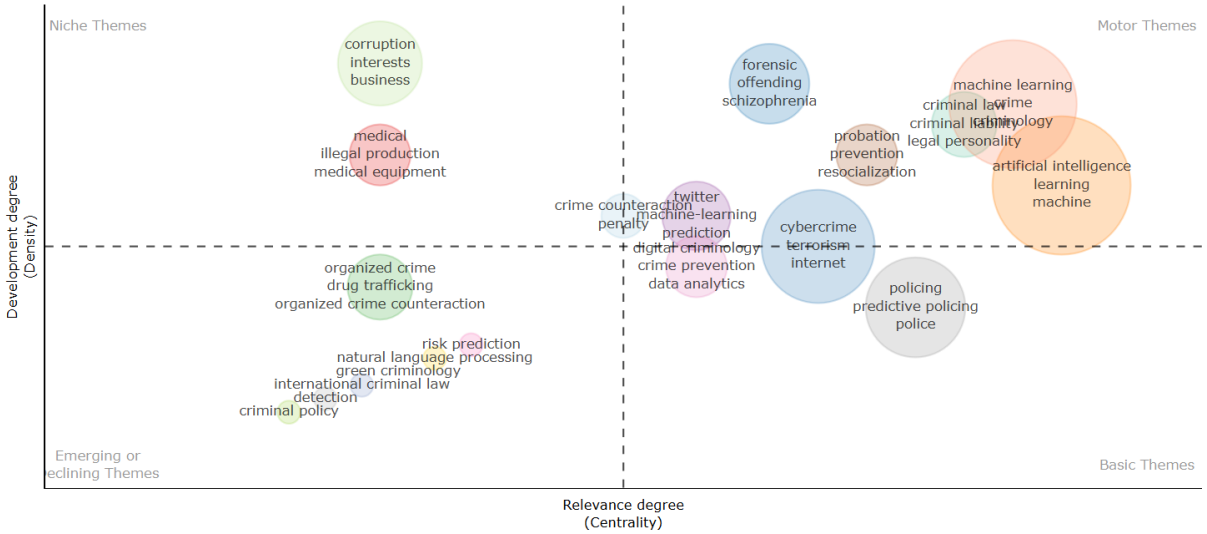
Figure 7. Clustering by Coupling



Clustering analysis of author collaborations reveals four principal thematic groups within the intersection of criminology and technology. The first cluster focuses on technological applications, with "Artificial Intelligence" emerging as a central label (90.9% confidence), reflecting work on AI integration for crime prediction and data analysis. The "modular learning" label (95.5% confidence) indicates the application of machine learning frameworks to criminological questions. The term "prime" appears in two clusters with confidence levels of 57.1% and 100%, signifying dual usage, either linked to prime-number algorithms or prioritised crime categories. These findings highlight the nuanced and multifaceted use of technology in criminological research (Aria & Cuccurullo, 2017).

A second cluster emphasises interdisciplinary research bridging criminology, law, and sociology. The "effending" label (100% confidence, likely "offending") denotes studies on criminal behaviour and offender profiling, while "conflict" (100% confidence) represents sociological perspectives on crime as a conflict-driven phenomenon. The third cluster links to medical and economic domains, with labels like "medical" (60%) and "medical equipment" (66.7%) relating to forensic and addiction research, and "business" (100%) pointing to economic and corporate crime. A potential typographical artifact, "copimodity monetary relations," may denote "commodity monetary relations," referencing financial crime. The fourth cluster exposes data quality concerns, with terms such as "sizingmental" and "illogal prediplinism" likely resulting from text-processing errors. Figure 8 visualises these conceptual structures using Author's Keywords and the Walktrap algorithm, optimised for balanced spatial representation.

Figure 8. Thematic Map

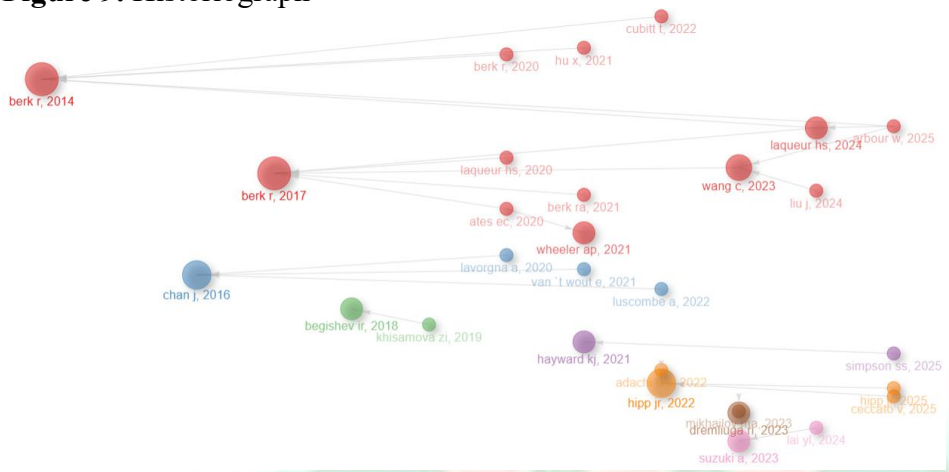


Basic themes in the literature represent widely studied topics with robust interdisciplinary connections, such as "crime prevention," "data analytics," "policing," and "predictive policing," all illustrating the pervasive use of AI and machine learning in preventive strategies, data-driven law enforcement, and algorithmic crime forecasting. Terms like "cybercrime," "terrorism," and "internet" highlight the technological dimension of modern criminology, particularly in addressing digital crimes and terrorism. Motor themes, representing mature and central research areas, include "machine learning," "criminal law," and "artificial intelligence," focusing on AI/ML's integration in legal systems and accountability. Terms such as "reconciliation learning," "organised crime," "drug trafficking," and "counteraction" reflect AI's strategic value in network analysis and transnational crime prevention. Emerging or declining themes, such as "natural language processing (NLP)," "green criminology," and "international criminal law," signal the field's evolving intersections with environmental, forensic, and psychological research. Niche themes like "corruption," "business interests," and "medical equipment" indicate underexplored yet promising areas for AI applications in economic and medical-sector crimes (Aria & Cuccurullo, 2017).

Intellectual Finding

In Figure 9, the historiographer has created a structure limited to 20 nodes, excluding isolated nodes and including only connected studies. Each node represents a study, and the labels are displayed in a short identity format as "1st Author, Year." To improve visual readability, the label size was set to 3 and the node size to 4. This structure clearly shows how fundamental studies in the field influence each other and the chronological development of the literature.

Figure 9. Historiograph



The analysis reveals that the most frequently cited publications - those exerting the strongest influence on subsequent research-prominently feature multiple works by author Berk. Particularly noteworthy are Berk's publications from 2014 and 2021, demonstrating this researcher's consistent and impactful contributions to the field. The documents found to be most influential on other studies are Berk (2014) and Berk (2017). These seminal works appear to have inspired subsequent research, with Berk (2014) influencing Laqueur (2023) and Berk (2017) serving as the foundation for Wang's (2023) work.

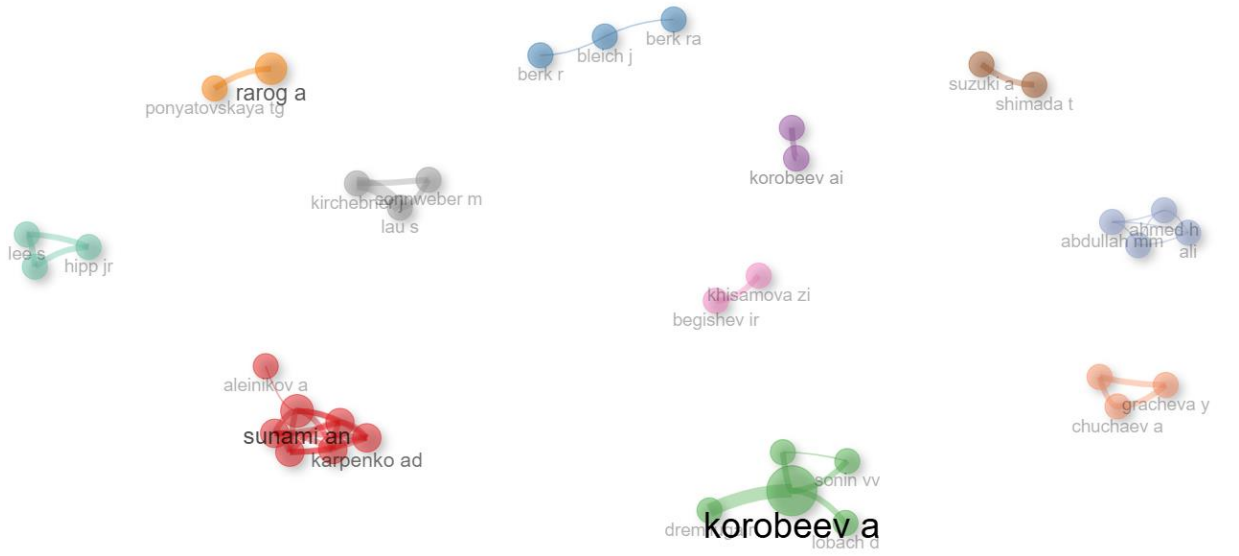
Social Finding

Figures 10 (Authors), Figures 11 (Institutions) and Figure 12 (Countries) display the collaboration network. In the analysis, the "Authors", "Institutions", and "Countries" fields were selected, and the "Avoid Label Overlap" option was enabled to prevent overlapping labels. An automatic layout was used to construct the network structure, and the Walktrap clustering algorithm was preferred for identifying sub-communities. Link normalization was performed using the "association" method, with a maximum of 50 nodes (authors) included in the network. To enhance visual distinction between nodes, a repulsion force of 0.1 was applied, and isolated (unconnected) nodes were removed from the network. Only nodes with at least one edge were included to preserve the connected structure of the network. In terms of visualization parameters, node opacity was set to 0.7, the label count was adjusted to 1000, and to improve readability, the label size was set to 2 with label visibility kept active. Nodes were represented as dots, with an edge thickness of 5, a shadow effect applied to nodes, and node editing disabled. These settings ensure a clear and comprehensible visual representation of collaborative relationships among authors.

Figure 10. Collaboration Network by Authors

Node	Cluster	Betweenness	Closeness	PageRank
Sunami	1	5	0.167	0.036
Aleinikov	1	0	0.143	0.03
Gazimagomed	1	0	0.143	0.03
Gazimagomedov	1	0	0.143	0.03
Karpenko	1	0	0.143	0.03
Strebkov	1	0	0.143	0.03
Aleinikov	1	0	0.091	0.007

Berk	2	0	0.333	0.021
Bleich	2	1	0.5	0.041
Korobeev	3	5	0.25	0.059
Dremliuga	3	0	0.143	0.021
Esakov	3	0	0.167	0.021
Lobach	3	0	0.143	0.015
Sonin	3	0	0.167	0.021
Korobeev	4	0	1	0.028
Dremliuga	4	0	1	0.028
Rarog	5	0	1	0.028
Ponyatovskaya	5	0	1	0.028
Shimada	6	0	1	0.028
Suzuki	6	0	1	0.028
Begishev	7	0	1	0.028
Khisamova	7	0	1	0.028
Kirchebner	8	0	0.5	0.03
Lau	8	0	0.5	0.03
Sonnweber	8	0	0.5	0.024
Lee	9	0	0.5	0.028
Hipp	9	0	0.5	0.028
Kim	9	0	0.5	0.028
Chuchaev	10	0	0.5	0.028
Gracheva	10	0	0.5	0.028
Malikov	10	0	0.5	0.028
Abdullah	11	0	0.333	0.028
Ahmed	11	0	0.333	0.028
Al-maeeni	11	0	0.333	0.028
Ali	11	0	0.333	0.028



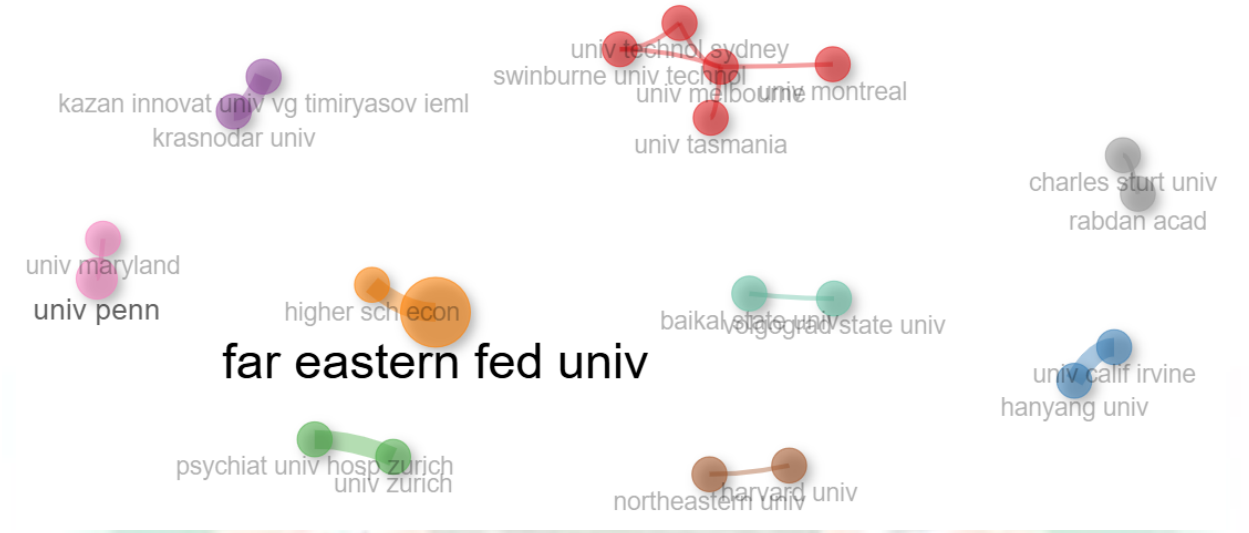
This table presents the centrality measures and clustering structure of nodes within a social network. The "Cluster" column denotes the group assignment for each node, while "Betweenness", "Closeness", and "PageRank" assess nodal importance using distinct metrics. Cluster 1 contains the largest cohort (e.g., Sunami, Aleinikov, Gazimagomed), suggesting a central or densely interconnected subnetwork. In contrast, Clusters 2, 3, and others comprise fewer nodes, often indicating more autonomous or specialised roles. Notably, nodes in Clusters 4–7 show Closeness centrality values of 1, signifying high accessibility and the ability to reach other nodes through short paths (Aria & Cuccurullo, 2017).

Regarding Betweenness centrality, Sunami (Cluster 1) and Korobeev (Cluster 3) lead with values of 5, marking them as crucial bridges for network communication. Bleich (Cluster 2) also holds significance (value 1), while others have values of 0, reflecting limited bridging function. For Closeness centrality, nodes in Clusters 4–7, such as Korobeev, Dremliuga, and Shimada, achieve the highest values (1), highlighting their efficient network positioning. Conversely, Cluster 1 nodes display lower Closeness values (0.091–0.167), indicating localized influence. PageRank results show Korobeev (0.059) as the most influential, followed by Sunami and Bleich, while others register moderate influence (0.02–0.03).

Figure 11. Collaboration Network by Institutions

Node	Cluster	Betweenness	Closeness	Pagerank
University of Tasmania	1	0	0.143	0.027
Swinburne University of Technology	1	0	0.167	0.046
University of Melbourne	1	5	0.25	0.092
Université de Montréal	1	0	0.143	0.027
University of Technology Sydney	1	0	0.167	0.046
University of California. Irvine	2	0	1	0.048
Hanyang University	2	0	1	0.048
Psychiatric University Hospital Zurich	3	0	1	0.048
University of Zurich	3	0	1	0.048
Krasnodar University	4	0	1	0.048
Kazan Innovative University	4	0	1	0.048

Far Eastern Federal University	5	0	1	0.048
HSE University	5	0	1	0.048
Northeastern University	6	0	1	0.048
Harvard University	6	0	1	0.048
University of Pennsylvania	7	0	1	0.048
The University of Maryland	7	0	1	0.048
Charles Sturt University	8	0	1	0.048
Rabdan Academy	8	0	1	0.048
Volgograd State University	9	0	1	0.048
Baikal State University	9	0	1	0.048



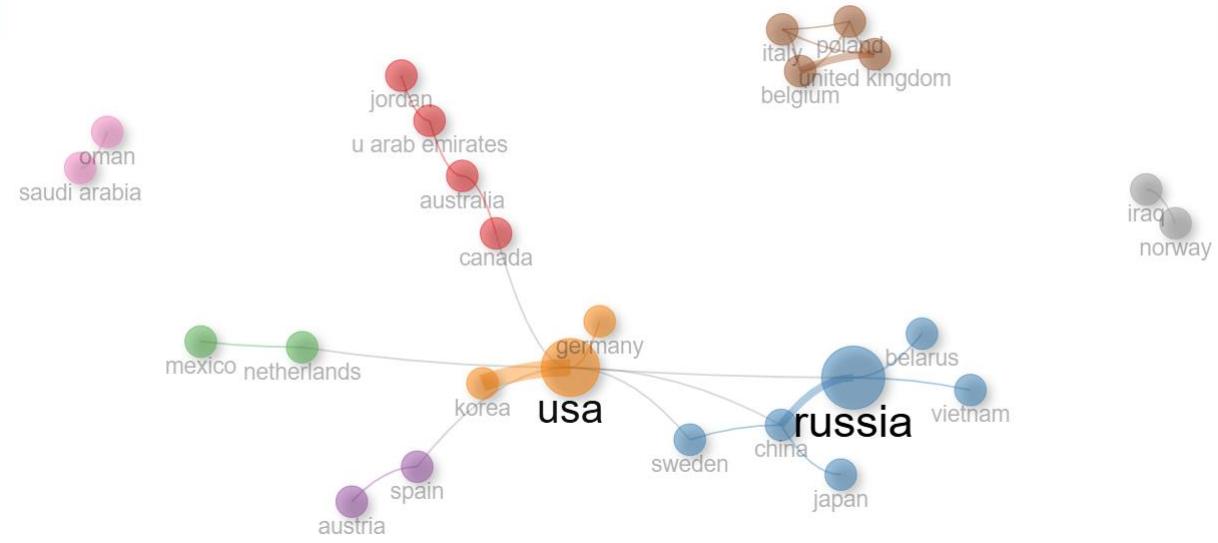
Cluster 1 comprises the largest group of universities, with the University of Melbourne emerging as the most central node, evidenced by a betweenness score of 5. Clusters 2 through 9 typically feature paired institutions (e.g., Harvard–Northeastern, Maryland–Pennsylvania), reflecting bilateral or localised collaborations. The University of Melbourne is the only institution with a significant betweenness value, highlighting its role as a crucial "bridge-builder" in academic partnerships. All other institutions have a betweenness of zero, indicating minimal influence in mediating information flow. Institutions outside the main cluster possess a closeness value of 1, suggesting optimal accessibility, while those within the main cluster display lower closeness (0.143–0.25), implying more localised impact (Aria & Cuccurullo, 2017).

The University of Melbourne also holds the highest PageRank value (0.092), signifying either strong connectivity or association with prominent institutions. Other universities display comparable PageRank values between 0.027 and 0.048, reflecting relatively equal standing within the network. These results underscore the University of Melbourne's position as the leading node in both betweenness and PageRank, acting as a central hub for international academic collaboration. While institutions outside the main cluster exhibit high closeness, their low betweenness underscores accessibility without intermediary influence. The generally low PageRank values across the network suggest a decentralised collaborative structure, with Melbourne uniquely positioned at its centre.

Figure 12. Collaboration Network by Countries

Country	Cluster	Betweenness	Closeness	PageRank

Australia	1	28	0.021	0.039
Canada	1	39	0.028	0.034
United Arab Emirates	1	15	0.017	0.043
Jordan	1	0	0.013	0.024
Russia	2	29	0.028	0.073
Japan	2	0	0.02	0.018
China	2	17	0.028	0.07
Sweden	2	0	0.025	0.03
Belarus	2	0	0.02	0.018
Vietnam	2	0	0.02	0.018
Netherlands	3	15	0.025	0.036
Mexico	3	0	0.018	0.021
Spain	4	15	0.025	0.036
Austria	4	0	0.018	0.021
Usa	5	98	0.037	0.138
Korea	5	0	0.024	0.041
Germany	5	0	0.024	0.018
United Kingdom	6	0	0.333	0.045
Italy	6	0	0.333	0.035
Belgium	6	0	0.333	0.045
Poland	6	0	0.333	0.035
Saudi Arabia	7	0	1	0.04
Oman	7	0	1	0.04
Iraq	8	0	1	0.04
Norway	8	0	1	0.04



Cluster I features Canada (39) and Australia (28) as prominent nodes with high betweenness values, while the United Arab Emirates (15) displays moderate betweenness. Cluster 2 is dominated by Russia (29) and China (17), both serving significant bridging functions within the network. In Cluster 5, the United States (98) exhibits the highest betweenness value overall, underscoring its role as the primary conduit for information and academic interaction. Cluster

6 sees the United Kingdom, Italy, Belgium, and Poland each with a closeness score of 0.333, reflecting strong network accessibility. Clusters 7 and 8, including Saudi Arabia, Oman, Iraq, and Norway, all achieve a closeness value of 1, indicating optimal reachability across the network (Aria & Cuccurullo, 2017).

In terms of betweenness centrality, the United States stands as the network's principal hub, controlling information flow, while Russia, Canada, and China also act as critical bridges. Countries such as Jordan, Japan, and Germany have zero betweenness, signifying no intermediary role. Closeness centrality highlights that nations in Clusters 7 and 8, with a score of 1, enjoy the shortest average distance to other nodes, although their influence—as shown by PageRank—remains modest. The United States (0.138) and Russia (0.073) lead in PageRank, reflecting their prestige, with China (0.070) and Canada (0.034) following. Despite high accessibility, Clusters 7 and 8 possess only average PageRank values (~0.040), suggesting limited overall network influence.

Discussion of Findings

A marked increase in publication output has been observed in the post-2019 period. This trend may be attributed to factors such as research team expansion, increased academic/funding resources, or growing scientific interest in the topic. The sharp spike in 2020, in particular, could reflect exogenous factors like the global COVID-19 pandemic. Such growth becomes especially significant when the research intersects with pandemic-related themes (e.g., health, technology, or digitalization).

Per Bradford's Law, researchers conducting literature reviews should prioritize examining the Russian Journal of Criminology (Zone 1), supplement with Zone 2 journals, and contextually evaluate Zone 3 sources. The data partially deviate from Lotka's Law, which anticipates a higher presence of prolific authors. For instance, only one author contributed six papers, indicating limited "high productivity" in the field. Potential reasons for this discrepancy include; Narrow dataset scope (e.g., single-journal/short-timeframe focus) and discipline-specific publishing norms (e.g., lower individual productivity in social sciences vs. natural sciences). Poor fit of Lotka's original inverse-square (n^2) model, suggesting alternative models may be warranted.

The bibliometric analysis reveals this interdisciplinary field as rapidly evolving and open to international collaboration. A 15.79 per cent annual growth rate in publications confirms rising academic interest. Post-2019 acceleration signals increasing adoption of AI applications in criminology, with frequent keyword occurrences (e.g., machine learning, cybercrime, predictive policing) underscoring its technology-driven, applied focus. While studies predominantly involve interdisciplinary teams, the 16.08 per cent international co-authorship rate indicates moderate but expandable global engagement. The dominance of the Russian Journal of Criminology suggests regional research concentration, whereas the U.S.'s central role in collaboration networks highlights its pivotal position in the global ecosystem.

Theoretically, AI-criminology research falls into four thematic groups; Technological applications (motor themes: machine learning/AI, indicating maturity), Law-sociology intersection, medical-economic disciplines and data quality issues (emerging themes like green criminology represent developing areas for future research). AI's integration into criminology is accelerating but remains in early stages, with distinct opportunities for thematic and collaborative expansion.

The bibliometric and thematic findings of this study align closely with the reviewed literature, providing a comprehensive overview of the evolving intersection between AI and criminology. A notable increase in publication output post-2019, particularly in 2020, reflects a broader academic

response to global disruptions such as the COVID-19 pandemic, which accelerated digitalization and technological reliance in many fields, including criminology. This surge corresponds with heightened scholarly engagement in AI-related themes-echoing the emphasis of Berk and Bleich (2014) and Berk (2017) on the practical utility of ML for sentencing and parole decisions under infrastructural constraints. Similarly, the expansion of research teams and international collaborations, though still moderate, points to the interdisciplinary nature of this field, as highlighted by Chan and Bennett-Moses (2016), who caution against overestimating Big Data's transformative impact without theoretical grounding.

The modest fit to Lotka's Law, revealing few prolific authors, may result from the field's emerging status and interdisciplinary structure, where collaborative rather than individual productivity dominates, an observation reinforced by Hayward et al. (2021) and Hipp et al. (2021), who demonstrated the applied, team-based nature of AI-crime studies. Keyword analysis and thematic mapping of the literature identified machine learning, cybercrime, and predictive policing as dominant, mature areas, corroborated by Wheeler and Steenbeek's (2021) findings on ML's micro-level crime prediction power.

At the same time, emergent areas such as green criminology and AI regulation echo concerns raised by Begishev and Khisamova (2018) and Mikhailov and Kokodey (2023), who stress the socio-legal implications of autonomous AI and call for regulatory innovations. Despite promising applications, the literature also revealed persistent challenges, including algorithmic fairness and interpretability, as underscored by Wang et al. (2023). Therefore, the integration of AI in criminology, while accelerating, remains theoretically and ethically complex, requiring sustained interdisciplinary collaboration and critical reflection.

Conclusion

This study examined the intersection of AI, ML, and language learning models within the field of criminology. The findings revealed a rapidly growing and interdisciplinary field marked by increasing scholarly interest, particularly after 2019, driven in part by global events like the COVID-19 pandemic and the expanding role of digital technologies in crime and justice. Despite the promising integration of AI tools such as ML and predictive analytics into criminological research and practice, the analysis highlights several limitations, including a lack of theoretical grounding, limited international collaboration, and underrepresentation of certain regions and voices. The dominance of applied, data-driven studies underscores the practical relevance of AI in addressing crime, yet it also calls for greater attention to ethical concerns, transparency, and the development of robust legal and regulatory frameworks.

Furthermore, the partial alignment with established bibliometric laws, such as Lotka's and Bradford's, suggests that the field is still in its formative stages, requiring more cohesive scholarly engagement. As AI continues to reshape criminology's methodological and conceptual boundaries, future research must strive for deeper theoretical integration, equitable global participation, and a balanced focus on both technological innovation and social accountability. In doing so, the field can move beyond its current paradigms to foster a more holistic and impactful approach to understanding and addressing crime in the digital age.

Recommendations

Based on the findings of this study, several recommendations are proposed to advance research and practice at the intersection of AI and criminology:

1. Future research should promote stronger collaboration between computer scientists, criminologists, legal scholars, and ethicists. Such interdisciplinary partnerships will ensure

that AI tools are not only technically sound but also socially and legally responsible, addressing both predictive accuracy and ethical implications.

2. The dominance of certain regional journals and relatively low international co-authorship rates suggest the need to broaden global engagement. Encouraging participation from underrepresented regions will enrich the diversity of perspectives, improve contextual relevance, and promote more globally applicable AI-criminology solutions.
3. Despite the field's applied focus, more effort should be made to integrate criminological theories with AI applications. Drawing from frameworks such as routine activity theory, strain theory, and environmental criminology can guide the development and evaluation of AI-driven tools within established criminological paradigms.
4. The increasing adoption of complex ML models calls for a parallel emphasis on model interpretability, especially in sensitive areas like risk assessments and predictive policing. Building interpretable models-as demonstrated in recent literature-will improve trust, fairness, and accountability in the justice system.
5. Given AI's capacity for misuse and unintended consequences, it is essential to establish clear ethical guidelines and regulatory standards. Policymakers and researchers must work together to define accountability structures, particularly concerning algorithmic bias, data privacy, and the criminal use of AI technologies.
6. Most current studies are exploratory or cross-sectional. Future research should adopt longitudinal designs to evaluate the long-term effectiveness and societal impacts of AI interventions in criminology, particularly in areas such as community policing, recidivism reduction, and digital crime prevention.

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