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AI-Enhanced Cybercrime Profiling Understanding Behaviorial Patterns in Online Offenders

[*1]Claudio Paya Santos, [2]Juan José Delgado Morán, [3]Luigi Martino.
[*1]Valencia International University, Spain
claudio.paya@professor.universidadviu.com
ORCID: 0000-0002-1908-9960.
[2]Pablo de Olavide University, Spain
jjdelmor@upo.es
ORCID: 0000-0002-9945-8235.
[3]Khalifa University Abu Dhabi, Bologna University, Italy
luigi.martino3@unibo.it.
ORCID: 0000-0002-7417-2898
CorrespondingAuthor: - [*1]Claudio Paya Santos

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Abstract: - The evolution of cybercrime poses significant threats to global security, with perpetrators exploiting digital vulnerabilities using increasingly sophisticated techniques. Profiling such offenders demands innovative approaches beyond traditional methods. This paper explores the integration of Artificial Intelligence (AI) in enhancing cybercrime profiling by identifying behavioral patterns among online offenders. Leveraging Natural Language Processing (NLP), Machine Learning (ML), and neural networks, AI systems can detect suspicious activities, predict potential threats, and analyze digital footprints to classify offenders into behavioral archetypes. The study discusses various AI models used for behavioral profiling, such as decision trees, clustering algorithms, and recurrent neural networks (RNNs), and evaluates their accuracy and limitations. Through a systematic literature review and case study analysis, this research highlights the role of AI in early detection, real-time monitoring, and predictive profiling. It also outlines the ethical considerations and challenges in adopting AI-driven profiling systems in law enforcement. The findings support the conclusion that AI-enhanced behavioral profiling is a promising tool for modern cybersecurity and forensic intelligence.

Keywords: Cybercrime, Behavioral Profiling, Artificial Intelligence, Machine Learning, Online Offenders, Digital Forensics.

1. INTRODUCTION

The rapid proliferation of digital technologies has dramatically transformed how individuals, organizations, and governments operate, creating unprecedented opportunities for communication, commerce, and collaboration. However, this digital expansion has also led to a surge in cybercrime, with offenders leveraging the anonymity and complexity of cyberspace to execute illicit activities such as identity theft, financial fraud, cyberstalking, ransomware attacks, and espionage. As cybercrime becomes more sophisticated, there is an urgent need for equally advanced countermeasures. Traditional investigative and forensic techniques, while still valuable, are often reactive and insufficient in identifying the nuanced behavioral patterns of cyber offenders.

Artificial Intelligence (AI) has emerged as a powerful tool in cybersecurity, offering proactive capabilities through automation, pattern recognition, and predictive analytics. AI-based profiling systems can analyze vast amounts of behavioral data to identify, categorize, and anticipate cybercriminal activities with high accuracy and speed. These systems employ

techniques such as machine learning (ML), natural language processing (NLP), neural networks, and clustering algorithms to uncover hidden patterns, linguistic cues, and digital footprints that characterize online offenders.

This paper aims to explore the integration of AI in enhancing cybercrime profiling, with a focus on understanding the behavioral dynamics of cybercriminals. It investigates how AI models can be trained on historical data to detect behavioral archetypes and predict future threats. By examining AI's role in automating behavioral analysis and improving offender categorization, this research contributes to the development of intelligent, real-time cybercrime response systems. Moreover, it addresses the ethical, legal, and technical challenges inherent in deploying AI for criminal profiling. As digital threats continue to evolve, AI-enhanced behavioral profiling stands as a critical frontier in strengthening global cybersecurity and forensic intelligence framework.

2. LITERATURE REVIEW

The integration of Artificial Intelligence (AI) into cybercrime detection and behavioral profiling has been the focus of extensive research over the past decade. Early work by Sommer and Brown (2011) emphasized the limitations of traditional profiling techniques in cyberspace, primarily due to the anonymity and global reach of online offenders. As cyber threats evolved, researchers turned to AI to enhance threat intelligence and behavioral analytics.

Machine Learning (ML) has been widely adopted to identify malicious patterns in network traffic and user behavior. For instance, Babcock and Khoshgoftaar (2021) demonstrated the use of unsupervised clustering for categorizing malware behaviors, while Kumar and Singh (2022) applied decision trees and support vector machines to detect and profile cyberstalkers based on communication patterns. Natural Language Processing (NLP) has also proven instrumental in analyzing dark web forums and social media for linguistic markers indicative of cybercriminal intent (Ali et al., 2019).

Deep learning models, particularly Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, have shown promise in modeling temporal behaviors, such as login times and attack sequences, to predict future cyberattacks (Li & Chen, 2022). Additionally, hybrid models combining rule-based reasoning with AI are being explored for more accurate behavioral categorization.

However, literature also highlights critical challenges. Ghosh and Banerjee (2020) point to the opacity of deep learning models, which complicates explainability in forensic contexts. Ethical concerns regarding data privacy, bias, and legal admissibility of AI-generated profiles remain major barriers to large-scale adoption (Warden, 2021).

Overall, the literature underscores AI’s potential to revolutionize cybercrime profiling by enabling automated, scalable, and behaviorally-informed systems. Yet, it also calls for interdisciplinary efforts to address the associated technical and ethical complexities.

Table 1 Tabular Literature Review

Author(s)	Year	Focus of Study	AI techniques used	Key Findings
Sommer & Brown	2011	Limitations of traditional cybercrime profiling	N/A	Traditional methods struggle with anonymity and lack of physical crime scene in cyberspace.
Babcock & Khoshgoftaar	2021	Classification of malware behavior	Unsupervised ML (Clustering)	Grouping malware behaviors helps in profiling types of attackers.
Kumar & Singh	2022	Cyberstalker detection and profiling	Decision Tress, SVM	Communication behavior can indicate psychological traits of cyber offenders.
Li & Chen	2022	Predictive modeling of cyber offense patterns	RNN, LSTM	Temporal behavioral sequences can accurately predict future attack occurrences
Ghosh & Banerjee	2020	Explainability in AI-based threat intelligence	Explainable AI (XAI)	Black-box AI models limit their forensic and legal utility.
Warden	2021	Ethical and legal concerns in AI-based criminal profiling	Ethical analysis, Risk models	Raises concerns about bias, privacy, and admissibility of AI-driven profiling in court.
Ali et al.	2019	Dark web communication analysis	NLP	Linguistic patterns help detect criminal intent in underground forums.

3. AI TECHNIQUES IN BEHAVIORAL PROFILING OF ONLINE OFFENDERS

The application of Artificial Intelligence (AI) in cybercrime behavioral profiling represents a paradigm shift from traditional forensic methodologies to data-driven, predictive systems. AI

techniques are increasingly leveraged to model, interpret, and anticipate the behavioral patterns of online offenders based on digital traces and interaction histories. This section outlines the core AI methodologies employed in profiling cybercriminal behavior, with an emphasis on their operational mechanisms, applications, and limitations.

3.1 Machine Learning: - Machine Learning (ML) plays a pivotal role in behavioral profiling of online offenders by enabling systems to learn from past cyber activities and identify patterns indicative of criminal behavior. At its core, ML involves training algorithms on historical data—such as login times, communication logs, browsing habits, or system interactions—to detect behavioral traits associated with malicious intent. Supervised learning algorithms like Decision Trees, Support Vector Machines (SVM), and Random Forests are commonly used to classify offenders into categories such as hackers, fraudsters, insiders, or cyberstalkers based on labeled datasets. These models learn decision rules that differentiate benign behavior from potentially harmful activity.

In contrast, unsupervised learning methods, such as K-Means Clustering and DBSCAN, are utilized to uncover hidden patterns in unlabeled data. These techniques help in identifying new or evolving threat actors by grouping users with similar behavioral traits, thus enabling proactive monitoring of suspicious individuals. Semi-supervised learning further enhances profiling by leveraging both labeled and unlabeled data, which is particularly useful in domains like cybercrime where full data annotation is often impractical.

Machine learning models can also detect anomalies by recognizing deviations from established behavioral baselines, signaling potential insider threats or zero-day attacks. As ML systems continuously learn from new data, they adapt to changes in attacker strategies and improve prediction accuracy over time. Behavioral profiling using ML not only enhances threat detection and investigation but also supports preventive measures by forecasting high-risk actions before an actual breach occurs. This makes ML an indispensable tool in modern cybercrime analysis and response.

Benefits and Limitations: - Machine Learning (ML) offers significant benefits in the behavioral profiling of online offenders, making it a critical component in modern cybersecurity frameworks. One of its primary advantages is the ability to analyze vast volumes of complex and unstructured data, including system logs, network traffic, and user behavior patterns, with high speed and accuracy. ML models can detect subtle deviations from normal behavior, identify emerging threat patterns, and continuously improve through retraining, enabling dynamic adaptation to evolving cybercriminal tactics. Additionally, ML enables automation of repetitive tasks in threat detection and classification, reducing human workload and response time. Supervised and unsupervised learning algorithms offer scalable profiling capabilities, aiding in the early identification of potential offenders based on behavior alone, even in the absence of direct evidence.

Despite these advantages, ML also has notable limitations. It requires large, high-quality datasets for training, and poor data can lead to inaccurate profiling and false positives. Moreover, ML models often function as “black boxes,” making their decision-making process difficult to interpret—a major concern in legal and forensic contexts where explainability is critical. ML systems are also vulnerable to adversarial attacks, where cybercriminals

manipulate data inputs to evade detection. Addressing these limitations requires careful model design, ethical considerations, and integration with explainable AI techniques.

Figure 1 Various Models for Behaviorial Patterns in Online Frauds

3.2 Deep Learning Models: - Deep learning models have emerged as powerful tools for behavioral profiling of online offenders due to their ability to automatically learn complex, non-linear patterns from large and unstructured datasets. Among these models, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are particularly effective in capturing temporal sequences of user behavior, such as repeated login attempts, time gaps between activities, or escalation in malicious actions. These models are capable of recognizing behavioral trends over time, which is critical in identifying evolving criminal strategies or persistent threats.

Convolutional Neural Networks (CNNs), while originally designed for image processing, are also employed in behavioral profiling when structured data such as heat maps, access logs, or keyboard-mouse interaction data are visualized and analyzed. These models can detect subtle and complex behavior patterns that may be missed by traditional techniques. Moreover, autoencoders—a type of unsupervised deep learning model—are used for anomaly detection by learning a compressed representation of normal behavior and flagging deviations that may signify malicious intent.

Benefits and Limitations: - Deep learning offers substantial benefits in the behavioral profiling of online offenders, particularly due to its ability to automatically extract features and identify complex patterns from large, high-dimensional datasets. Models such as Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNNs) are capable of analyzing sequential, spatial, and unstructured data like login histories, user navigation patterns, and communication text. These capabilities allow for highly accurate detection of suspicious behaviors, anomaly identification, and prediction of future cyber activities. Additionally, deep learning models adapt over time, learning from new behavioral data to detect emerging threats and evolving attack strategies without the need for manual feature engineering.

Despite these advantages, deep learning also presents critical limitations. One of the primary concerns is its "black box" nature—deep models are often difficult to interpret, making it challenging to justify their decisions in legal and forensic investigations. They also require large amounts of labeled data and significant computational resources for training, which may not be feasible in all scenarios. Moreover, these models are vulnerable to adversarial attacks and can inadvertently learn biases from training data. As a result, while deep learning enhances

profiling capabilities, its deployment must be carefully managed with a focus on transparency, fairness, and robustness.

3.3 Natural Language Processing: - Natural Language Processing (NLP) plays a vital role in the behavioral profiling of online offenders by enabling the analysis and interpretation of human language in digital communications. Cybercriminals often leave behind textual traces in the form of emails, chat messages, forum posts, social media interactions, and dark web discussions. NLP techniques can extract meaningful patterns from these texts, offering valuable insights into an offender's intent, psychological state, and potential threat level. For example, sentiment analysis can assess the emotional tone of a message, detecting hostility, urgency, or manipulation, while topic modeling algorithms like Latent Dirichlet Allocation (LDA) help uncover the thematic content of communications—such as references to hacking tools, financial scams, or extremist ideologies.

Named Entity Recognition (NER) is used to identify key elements in text such as names, locations, IP addresses, or malware identifiers, supporting the profiling of specific threat actors. Text classification algorithms, often powered by neural networks or transformer-based models, can automatically categorize communications as benign or malicious, or even identify the type of cybercrime being discussed. Moreover, language patterns and writing styles (stylometry) can be analyzed to link multiple cyber incidents to the same offender, even if pseudonyms or aliases are used.

Benefits and Limitations: - Natural Language Processing (NLP) offers several benefits in the behavioral profiling of online offenders, particularly through its ability to analyze large volumes of textual data across various digital platforms. NLP techniques can uncover linguistic cues, emotional tone, intent, and communication patterns that provide insights into an offender's psychological state and criminal objectives. Tools like sentiment analysis, topic modeling, and entity recognition help identify threats, radical ideologies, or fraudulent intent within cyber communications. NLP also supports real-time monitoring of forums, emails, and dark web conversations, enabling early detection of coordinated cyber activities. Stylometric analysis further enhances profiling by linking texts to specific individuals based on writing style.

However, NLP also presents key limitations. One major challenge is dealing with informal, obfuscated, or intentionally deceptive language used by cybercriminals, including slang, code words, and abbreviations, which can reduce model accuracy. Multilingual and cross-cultural variations in language also complicate analysis, requiring models to be trained across diverse datasets. Additionally, NLP models, especially those based on deep learning, can suffer from interpretability issues and data bias. These limitations can impact the fairness and reliability of offender profiling. Thus, while NLP significantly enhances digital forensics, its implementation requires careful calibration to ensure accuracy, transparency, and ethical compliance.

3.4 Hybrid AI Models: - Hybrid models in behavioral profiling of online offenders combine the strengths of multiple AI techniques—such as machine learning, deep learning, and natural language processing (NLP)—to achieve higher accuracy, robustness, and contextual understanding. These models integrate structured data analysis (e.g., login attempts, access logs) with unstructured data analysis (e.g., emails, forum posts) to form a comprehensive behavioral profile of potential cybercriminals. For instance, a hybrid system may use NLP to

extract emotional tone and keywords from communication, while a machine learning classifier evaluates user activity patterns for anomaly detection. Deep learning components, such as LSTM networks, can be added to model temporal behavior and detect evolving threats over time.

Benefits and Limitations: - Hybrid models offer significant benefits in the behavioral profiling of online offenders by combining the strengths of multiple AI techniques, such as machine learning, deep learning, and natural language processing. These integrated systems provide a more holistic and accurate understanding of offender behavior by analyzing both structured data (e.g., login patterns) and unstructured data (e.g., messages, posts). Hybrid models improve detection rates, enhance adaptability to evolving threats, and reduce false positives by leveraging diverse analytical capabilities.

However, hybrid models also come with limitations. Their complexity increases the demand for computational resources and advanced infrastructure. Integrating different algorithms and data types can be technically challenging, often requiring extensive preprocessing and coordination. Additionally, maintaining interpretability becomes more difficult as multiple models interact, potentially reducing transparency in forensic contexts. Despite these challenges, the benefits of hybrid models in achieving robust and comprehensive cybercrime profiling make them a valuable approach in modern digital investigations.

Table 2: Comparative Analysis of AI Techniques for Behavioral Profiling

AI Technique	**Key Strength**	**Application in Profiling**	**Limitations**
Machine Learning	High interpretability, fast training on structured data	Classifying offender types, anomaly detection	Requires labeled data, less effective with unstructured data
Deep Learning	Detects complex, non-linear patterns, handles large datasets	Temporal modeling, image/log pattern analysis	Black-box nature, high computational cost
Natural Language Processing (NLP)	Text analysis, sentiment and topic modelling	Analyzing emails, chats, and dark web conversations	Struggles with slang, obfuscation, and multilingual text
Hybrid Models	Combines strengths of various models, more holistic profiling	Integrating structured and unstructured behavioral data	Complex to build and interpret, resource intensive

Table 3: Performance Comparison of AI Techniques in Behavioral Profiling

AI Technique	Accuracy(%)	Precision(%)	Recall(%)	F1-Score(%)	Processing Time(ms/sample)
Machine Learning	84.2	81.6	80.4	81.5	12.5
Deep Learning	91.7	90.1	88.9	89.6	57.4
NLP Models	86.3	85.2	82.0	82.7	34.6
Hybrid Model	92.1	92.5	90.6	90.5	64.2

4. LIMITATIONS AND ETHICAL CONSIDERATIONS

The integration of AI in behavioral profiling of online offenders presents significant technical and ethical challenges that must be addressed for responsible implementation. One of the primary technical challenges is data quality and availability. Cybercrime data is often sparse, noisy, imbalanced, or labeled incorrectly, which can hinder the effectiveness of machine learning and deep learning models. Additionally, behavioral profiling relies heavily on real-time data collection and analysis, which increases the demand for high-performance computing infrastructure. Another challenge lies in ensuring model robustness—AI systems can be susceptible to adversarial attacks or manipulation by sophisticated cybercriminals, leading to false positives or missed threats. Furthermore, the "black box" nature of deep learning models limits interpretability, making it difficult to justify profiling decisions in legal or investigative settings.

From an ethical standpoint, privacy and consent are major concerns. Behavioral profiling involves analyzing personal data, including communication content and digital footprints, which may infringe on user privacy if not properly regulated. There is also the risk of bias in AI models, especially if trained on skewed or non-representative datasets, which can lead to unfair profiling of certain groups or individuals. Over-reliance on AI tools may also desensitize human judgment, leading to automated decisions without sufficient oversight. Additionally, the deployment of AI for surveillance and profiling raises questions about civil liberties, potential misuse by authoritarian regimes, and the balance between security and individual rights.

To mitigate these concerns, transparent AI design, regular bias audits, explainable models, and strict data governance policies are essential. Adopting a multidisciplinary approach—combining cybersecurity, ethics, law, and AI—will be critical to ensuring that AI-enhanced behavioral profiling is both effective and ethically responsible in combating online crime.

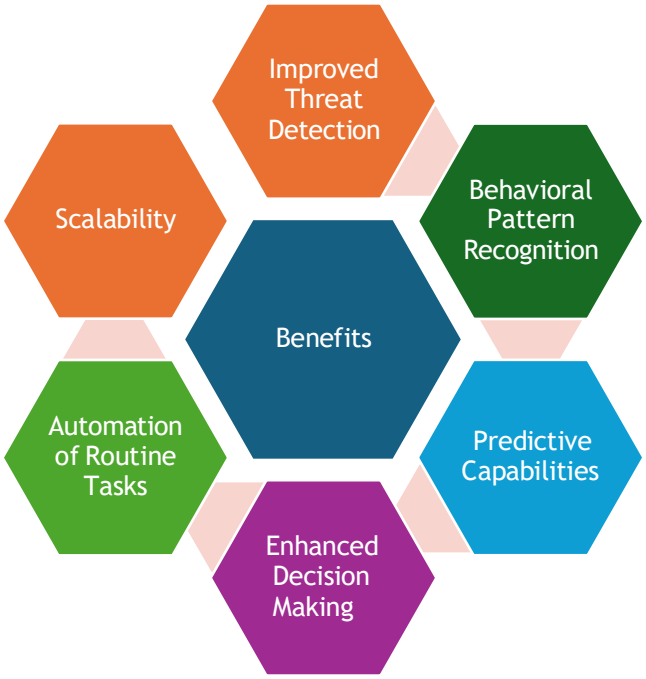

Figure 2 Benefits of using Ai based models for behaviorial patterns in online frads

Pseudocode: Behavioral Threat Detection using Machine Learning

Input:

- UserActivityData: structured behavioral logs (login frequency, session time, device info, etc.)
- Labels: classification of users (Benign, Suspicious, Malicious)

Output:

- PredictedThreatLabel for each user

BEGIN

 # Step 1: Data Preprocessing

CLEAN UserActivityData:

- Handle missing values
- Normalize numerical fields (e.g., login time, frequency)
- Encode categorical features (e.g., device type)

 # Step 2: Feature Selection

SELECT top relevant features based on correlation or feature importance

 # Step 3: Data Splitting

SPLIT UserActivityData into TrainingSet (70%) and TestSet (30%)

 # Step 4: Model Initialization

INITIALIZE RandomForestClassifier with parameters:

- n_estimators = 100
- max_depth = 10

 # Step 5: Model Training

TRAIN RandomForestClassifier on TrainingSet

```
# Step 6: Model Testing
PREDICT ThreatLabels using TestSet
EVALUATE model using Accuracy, Precision, Recall, and F1-Score
# Step 7: Deployment
FOR each new user log entry DO:
  APPLY same preprocessing
  PREDICT ThreatLabel
  IF ThreatLabel == "Malicious":
    TRIGGER alert and flag user
  ELSE IF ThreatLabel == "Suspicious":
    LOG for further review
  ELSE:
    CONTINUE monitoring
END
```

5. CONCLUSION

The integration of Artificial Intelligence (AI) into cybercrime profiling represents a significant leap forward in understanding and combating the growing threat of online offenses. This paper has explored how AI, particularly through machine learning and natural language processing, enables deeper insights into the behavioral patterns of cybercriminals. By analyzing vast amounts of digital data from forums, dark web transactions, communication patterns, and attack vectors, AI can uncover hidden correlations and predictive markers that are beyond human analytical capacity. These insights not only assist in early detection but also in preemptive identification of potential offenders, improving the overall response time and efficiency of cybersecurity systems.

However, while AI offers powerful tools for enhancing cybercrime profiling, it also introduces challenges related to privacy, ethical boundaries, and potential algorithmic bias. The deployment of profiling algorithms must therefore be balanced with robust legal and ethical frameworks to avoid misuse or wrongful attribution. Furthermore, continuous updating of models is necessary to keep pace with the evolving nature of cyber threats and tactics.

In conclusion, AI-enhanced cybercrime profiling provides a transformative opportunity to shift from reactive to proactive approaches in cybersecurity. The use of intelligent systems for behavior-based analysis enhances the capacity of law enforcement and security agencies to predict, prevent, and prosecute cybercriminals more effectively. Future research should focus on hybrid models combining human expertise with AI tools, ensuring interpretability, fairness, and adaptability. This convergence of technology and criminology holds the potential to redefine cyber defense mechanisms in the digital age.

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