

# AI-Assisted Criminal Investigations: Enhancing Testimony Analysis and Case Correlation

**Abstract**—This paper presents Lexa AI, a holistic AI-powered solution for improving criminal investigative practices through four phases, that target key drawbacks found in traditional practices. The first model provides an automated data/information collection stage that accepts legal documents in multiple formats that utilize a three-stage processing pipeline based on Gemini 2.0 Flash model, which performs Optical Character Recognition (OCR) with a higher level of accuracy and speed compared to alternative approaches. The collected data will be escalated to the next phase by leveraging dynamic question generation that uses Reinforcement Learning (RL), instantaneous multilingual capacity, and real time scoring of relevance. In the third phase Multimodal Behavioral and Physiological Analysis (MBPA) will be done, which includes facial signals, speech signals, and heart rate signals to create a combined Stress Index as an objective indicator, and without judgement. Finally, semantic similarity will be measured to correlate incidents, assess risk for victims, and provide explainable predictions.

**Keywords**—*Law Enforcement, Criminal Investigation, Automated Data Collection, Machine Learning, Legal Technology, Artificial Intelligence.*

## I. INTRODUCTION

Criminal investigations have been dependent in the past on conventional methods with features of manual documentation, subjective interpretation, and lengthy processes that usually yield conflicting records, lost behavioral leads, and long intervals of delay between pertaining cases. Such conventional methods impose enormous constraints on law enforcement agencies in trying to manage complicated criminal cases with numerous suspects, witnesses, and complex patterns of evidence [1].

The subjective effects of classical testimony examination, coupled with the overwhelming volume of unstructured legal texts and the difficulty of detecting nuanced behavioral patterns in interrogations, have generated a pressing need for technological intervention to enhance investigative ability [2], [3]. Current developments in Artificial Intelligence (AI) offer new solutions to these challenges in the form of advanced automated data extraction, adaptive questioning, large-scale behavioral analysis, and pattern recognition systems.

By combining machine learning algorithms, natural language processing, multimodal sensing technologies, and predictive analytics, AI provides unparalleled potential for

transforming criminal investigation techniques [4]. Through the utilization of these AI-based methods, investigations can become more effective, accurate, and unbiased, while still maintaining the necessary human oversight for judicial integrity.

This study presents Lexa AI, an end-to-end integrated platform with four unique AI-based models, designed to overcome the major pitfalls of conventional criminal investigation procedures. The platform reconfigures subjective, manual investigation methods into objective, automated processes without compromising investigator control or adherence to legal and ethical standards [5].

## II. LITERARY REVIEW

The use of artificial intelligence in criminal investigations represents a paradigm shift from traditional policing techniques to computerized, data-driven methodologies. This comprehensive review of the literature canvasses the evolution of AI technologies within law enforcement, applications, methodologies, strengths, and weaknesses, and the critical research gaps that necessitate the development of integrated AI systems for criminal investigations.

### A. Evolution of AI in Law Enforcement

Artificial intelligence, as it pertains to criminal investigation, has developed significantly from simple rule-based systems into sophisticated machine learning approaches. Early research by Choudhary established the foundations of AI methods in policing, suggesting expert systems that enhanced police administrative processes, evidence management, and fundamental decision-making procedures [1], [6]. Such initial systems demonstrated the ability of AI to "surface uncorrelated facts/inferences, detect patterns of criminality/conspiracy, consult on all legal aspects pertaining to investigations, and forecast criminality". Present research has expanded considerably from these original concepts. J Singh and P. Patel conducted a systematic review of 120 peer-reviewed articles that were published between 2008 and 2021 on AI techniques for crime forecasting in 34 types of crime and found it to be a massive expansion and diversification in the application of AI in criminal justice [7]. This demonstrates the overall greater technological advancement from deterministic rule-based AI to sophisticated machine learning models capable of processing enormous amounts of data and identifying complex patterns.

### B. Predictive Policing and Crime Prevention

One of the most extensive applications of AI in criminal investigation is predictive policing, where machine learning algorithms analyze historical patterns of crime and forecast

likely criminal activity [8]. The RAND Corporation's wide-ranging research has demonstrated that predictive policing can reduce crime rates by enabling law enforcement agencies to pre-deploy resources. This approach is a paradigm shift from reactive to proactive policing. University of Chicago studies made unbelievable progress, developing machine learning programs that foresaw crimes a week in advance with 90% accuracy. The research, however, did reveal unsettling biases in police behavior, wherein crimes in wealthy neighborhoods led to additional arrests and arrests in poverty-stricken neighborhoods went down, highlighting the need to address algorithmic bias in AI. The implementation of predictive policing software has had mixed results in practice [9]. The Chicago Police Department's Strategic Subject List (SSL) system used machine learning software to track historical patterns of crime and identify the most probable perpetrators of violent crime. But this system was heavily criticized as being biased in terms of data and for a lack of transparency, and it was ultimately deactivated in 2020 [6]. This case study embodies the main issues with implementing AI systems in sensitive law enforcement contexts.

### C. Behavioral Analysis and Interrogation Technologies

AI use in behavioral analysis for criminal interrogations is a crucial area of study, supplementing traditional methods like the Behavioral Analysis Interview (BAI). L. Robert's initial research established the BAI as "the sole questioning technique to have been developed specifically to help investigators differentiate between those who are likely to be guilty and those who are not [10]." Nevertheless, independent research conducted by B. Carter revealed significant limitations, discovering no significant difference between the response of innocent and guilty participants to most BAI behavior-evoking questions. Recent advances in multimodal behavioral analysis have been promising to mitigate these limitations [11]. Experiments on Criminal Emotion Detection Framework using Convolutional Neural Networks achieved great accuracy levels of 92.45% for crime detection and 98.6% for criminal emotion detection using LeNet-5 architecture. It is a significant step from traditional subjective observation techniques, providing objective, measurable estimates of behavioral markers. The integration of multimodal streams for behavior analysis has been of great interest. Research that has investigated multimodal behavior patterns using eye-tracking and Large Language Model-based inference has proven the power of combining various data sources so that deeper insights are attained than if one modality was used alone. These systems provide redundancy, with the potential to continue extracting useful information in case one modality fails, other data streams can replace it [10].

### D. Speech Emotion Recognition in Criminal Investigations

Speech Emotion Recognition (SER) is one of the main components of AI-aided criminal investigations. K. Varma have authored a systematic review highlighting applications in "lie detection and criminal investigations, medical diagnosis and monitoring, and robotic emotion expressions". The state-of-the-art SER systems employ cutting-edge deep neural network architectures, including CNN-BiLSTM models with attention mechanisms, reporting validation accuracies of 72% on datasets like

RAVDESS. Research into criminal emotional state detection has been promising regarding applying SER systems to identify emotional states that characterize deceit or guilt [12]. Deep learning approaches have made it possible to develop systems for processing live audio streams and providing real-time feedback to investigators. There are challenges in achieving performance stability across languages, accents, and emotional expression patterns [13].

### E. Natural Language Processing for Legal Documents

Natural Language Processing application to legal document analysis has also become increasingly sophisticated, responding to the unique requirements of formal legal language characterized by a specialized vocabulary, formality, and rigid syntactic patterns. Legal applications of NLP comprise document summarization, entity recognition, legal research automation, and sentiment analysis. Advanced NLP tools for legal texts employ techniques such as Named Entity Recognition (NER) and dependency parsing to efficiently locate and classify important entities such as individuals, organizations, dates, and legal jargon. These systems demonstrate exceptional performance in processing complex legal text, with some implementations performing better than conventional human analysis methods. Effort has also been put into developing domain-specific language models for legal applications [5], [12]. Legal-BERT and GPT-based legal text models have surpassed the use of general-purpose language models dramatically in areas such as contract valuation, case law summarization, and compliance verification. There are still challenges, however, regarding the unavailability of annotated legal data sets, difficulties interpreting domain-specific terminology, as well as model bias problems.

### F. Multimodal Fusion and Integration Challenges

Multimodal integration of multiple AI modalities is promising and challenging for criminal investigation. Recent literature has shown evidence of multimodal solutions in achieving more accurate and richer analysis than single-modality systems [9], [14]. Multimodal learning analytics for behavior analysis has been demonstrated through research that the fusion of video streams, audio analysis, and physiological signals can result in improved information about subject states and intentions. Multimodal systems have significant technical challenges even with the difficulties. The active research areas include synchronization of different data streams, handling data with different qualities, and algorithmic fusion optimization. Developing efficient fusion methods that can handle missing or degraded data within one modality without any degradation in system performance is a main challenge [14].

### G. Ethical Considerations and Algorithmic Bias

The use of AI in criminal investigations is a significant ethical concern that has been given more prominence in literature. Algorithmic bias has been showcased by studies as one of the main concerns, with empirical evidence demonstrating that AI systems have the capacity to perpetuate or amplify the already present bias in training data. The case study of Chicago SSL system well explains how algorithmic bias can be turned into discriminatory treatment in practice [15]. Privacy and surveillance

concerns are another field of study of utmost significance. The widespread application of AI technologies to law enforcement, like facial recognition, behavioral analysis, and predictive policing, brings into question some basic issues regarding civil rights and the interplay between individual rights and public safety. European studies have signaled the need for the AI application to be regulated and overseen with robust legal and regulatory controls.

#### H. Current Gaps and Research Limitations

Despite the large amount of research on the use of AI in criminal investigations, there are still several critical gaps. M. Johansson identified "limited evidence-based knowledge on the optimal use of AI for criminal investigations in literature," indicating the need for more holistic, integrated approaches. Current studies primarily focus on individual applications rather than holistic systems that would be able to address various problems in criminal investigations simultaneously [15]. The lack of standardized measuring approaches is another dominant gap [16]. Different measures, data sets, and criteria are employed in different studies, and therefore comparison of system performance and identification of best practices is challenging. Most studies also focus on laboratory conditions, rather than deployment environments, which limits the applicability of findings [13].

#### I. Integration and System Architecture Research

Recent research has already begun working on the need for end-to-end AI-driven systems in criminal investigations. N. Dunsin showcased extensive surveys of NLP applications to legal text like document summarization, named entity recognition, question answering, and argument mining [6]. The surveys illustrate the potential for end-to-end systems that can fulfill more than one investigative need simultaneously. However, research on system integration, workflow optimization, and human-AI collaboration in criminal investigations remains limited. Building end-to-end platforms that are capable of seamless integration of document processing, behavioral analysis, question generation, and pattern recognition is an important research area that has not been adequately examined through existing literature [8].

Literature clearly indicates some promising directions for research in future AI-assisted criminal investigations. Explainable AI that can provide transparent justification for selecting their actions is a fundamental necessity for legal deployment. Another line of study that must be pursued is human-AI collaboration models that preserve investigator control while optimizing use of AI functionalities. The convergence of emerging technologies, including advanced language models, multimodal fusion techniques, and real-time processing, promises to make more sophisticated and effective criminal investigation systems. Yet, convergence must be supplemented with serious attention to ethical considerations, bias reduction, and legality.

### III. METHODOLOGY

The proposed AI-augmented criminal investigation system mainly can be divided among four main components/phases.

They are

1. The Automated Data Collection and Management phase.
2. Dynamic Question Generation and Response Analysis phase.
3. Multimodal Behavioral and Physiological Analysis phase.
4. Incident Correlation and Pattern Identification phase.

It combines automated data extraction, adaptive questioning, behavioral analysis, and predictive correlation to provide an integrated platform that enhances the efficiency of investigation as well as its accuracy.

The overall system diagram presents the workflow of the proposed platform. At its center is the suspect, who acts as the hub of multimodal data acquisition. Inputs are gathered through three key channels: video streams for facial expression analysis, heart rate signals for physiological stress detection, and audio for speech emotion recognition and content extraction. These streams are processed by a multimodal fusion processor that combines them to create comprehensive behavioral analysis reports. This fusion provides more accurate stress evaluations than any single modality alone. Alongside these behavioral signals, the system integrates structured and unstructured inputs such as witness statements, new incident reports, and historical case data into an enhanced classification model. Two AI components drive the investigative workflow: the Question Generation Model, which produces interrogation questions based on case data and investigator feedback, and the Pattern Recognition Model, which identifies correlations and generates insights from prior cases. All system outputs including behavioral dashboards, dynamically created questions, and pattern-based findings are consolidated into a single investigator interface that ensures real-time decision support while maintaining investigator control.

The Automated Data Collection and Management phase forms the foundation of the platform and is designed to retrieve structured information from unstructured legal documents such as police reports and court orders written in both Sinhala and English. Processing begins with a SHA256 checksum to eliminate duplicate documents. Optical Character Recognition (OCR) is then used to convert diverse file formats including images, PDFs, and text files into machine-readable text. The system employs Google's Gemini 2.0 Flash as the primary large language model, supported by prompt engineering that guides entity extraction, interprets legal fields, and automatically translates Sinhala documents into English for consistency. Extracted information is then converted into a JSON schema and validated using Zod to guarantee type safety and data integrity. This triadic pipeline of OCR, structured data extraction, and predictive summarization ensures that investigators are provided with reliable structured outputs, including case summaries and predictive insights that flow seamlessly into the next phase.

The Dynamic Question Generation and Response Analysis phase establishes an adaptive interrogation support system that mimics the natural flow of real interviews through a four-stage pipeline. It supports both English and Sinhala, with speech-to-text and manual input modes. The first stage uses large language models to generate contextually relevant opening questions, adapting tone and content based on whether the subject is a victim or a suspect. The second stage performs response analysis, applying semantic similarity (cosine similarity of embeddings), dependency parsing, and Named Entity Recognition (NER) to assign numerical relevance scores from 0 to 10, extract facts, identify gaps, and recommend investigation priorities. The third stage generates follow-up questions that refine focus on timelines, motives, witnesses, and inconsistencies, using reinforcement learning strategies such as epsilon-greedy optimization. Investigators may override the AI and insert their own questions if desired. Finally, the fourth stage records all questions, responses, and relevance scores, while also tracking investigator choices about which generated model outputs were most useful. These feedback loops continuously refine the system, allowing adaptive learning policies to update questioning effectiveness across future interrogations.

The Multimodal Behavioral and Physiological Analysis phase integrates visual, auditory, and physiological signals to produce an objective Stress Index during interrogations. Facial expression recognition is employed because micro-expressions are important indicators of concealed emotions and credibility. The system uses a CNN architecture based on VGG-16, trained on the FER-2013 dataset. Inputs are grayscale 48×48 crops of facial regions, processed at 25–30 frames per second with preprocessing steps including alignment and normalization. Data augmentation techniques such as rotation, flipping, brightness adjustment, and Gaussian noise expand the dataset, providing robustness against variability in real interrogation settings. Speech emotion recognition employs a CNN-BiLSTM with attention mechanism, trained on the RAVDESS dataset. Audio inputs of 2–3 seconds (22.05 kHz) undergo denoising, voice activity detection, and feature extraction (MFCC, chroma, and contrast), with augmentation including pitch variation, time stretching, and background noise injection. Heart rate variability analysis uses AD8232 ECG sensors, applying band-pass filtering and R-peak detection to derive classical explainable features such as RMSSD, SDNN, LF/HF ratio, and Baevsky Stress Index. These three modalities are combined using a fusion equation defined as:

$$S = \text{SHRV} + \text{SEMO} \times (1 - q)$$

Equation 1 Fusion Equation

where SHRV represents the HRV-derived stress score, SEMO is the fused emotion score from FER and SER, and  $q$  is a modality-specific quality factor. Exponential Moving Average (EMA) smoothing ensures temporal stability, while synchronized timestamps across all modalities maintain near real-time responsiveness with a latency of less than two seconds.

The Incident Correlation and Pattern Identification phase processes both structured and unstructured features to

predict criminal responsibility and identify related cases. Structured features such as victim and perpetrator age, age differences, gender, type of violence, and evidence availability are numerically encoded through feature engineering. Unstructured narratives are embedded using Sentence-BERT (all-MiniLM-L6-v2) and compared against a case corpus using cosine similarity, returning the top three most similar cases with options for recency filtering. A Random Forest classifier predicts criminal responsibility categories Likely Criminal, Likely Victim, or Inconclusive based on structured inputs, while semantic similarity scores enrich this with contextual insights from testimony. Risk levels for victims are also quantified (Low, Medium, High, Critical). This entire workflow is served via FastAPI microservices with MongoDB persistence, and investigators interact with a Next.js interface that integrates behavioral dashboards, case correlations, and interrogation records in one place.

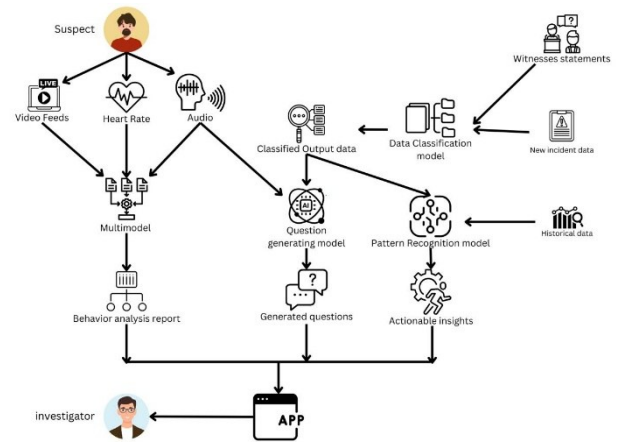


Fig 1 System Architecture

## IV. RESULTS AND DISCUSSION

### A. Automated Data Collection and Management

The first phase successfully converted unstructured and noisy legal documents such as police reports and court orders into structured, standardized data objects. The three-stage pipeline Optical Character Recognition (OCR), schema-driven entity extraction, and JSON schema validation produced high-fidelity outputs that captured case identifiers, incident details, victim/suspect profiles, and evidence references. When evaluated on the FUNSD dataset (Form Understanding Noisy Scanned Documents) [16], Google Gemini 2.0 Flash achieved an accuracy of 83.51%, outperforming OpenAI GPT-4o (81.58%). It also demonstrated faster average processing times (5,049 ms vs. 11,903 ms) and a significantly lower Character Error Rate (21.30% vs. 44.10%). In addition to structured fields, the system generated narrative summaries and predictive statements about potential legal outcomes. These findings highlight the model's capacity to overcome inefficiencies of paper-driven records and establish a digital-first baseline for criminal case management.

### B. Dynamic Question Generation and Response Analysis

The second phase provided adaptive interrogation support and was evaluated in both simulated and naturalistic

settings. It consistently generated context-sensitive opening questions, adjusting tone and depth depending on whether the subject was a victim or a suspect. Responses were captured via speech-to-text or manual entry in both English and Sinhala, and each was scored on a 0–10 relevance scale. Reinforcement learning techniques, particularly epsilon-greedy optimization, improved the selection of follow-up questions by adapting to investigator preferences and prior response quality. Importantly, the option for manual override preserved investigator autonomy while benefiting from automation. Field trials demonstrated that the system reduced preparation time, improved lead identification, and increased interrogation consistency, confirming its utility as a hybrid model that blends automation with human oversight.

### C. Multimodal Behavioral and Physiological Analysis (MBPA)

The third phase integrated facial expression recognition (FER), speech emotion recognition (SER), and heart rate variability (HRV) into a combined Stress Index (0–100), offering investigators real-time insights into credibility and emotional states. Performance evaluation showed:

- **FER (VGG-16 on FER-2013):** 63% accuracy in classifying emotions.
- **SER (CNN-BiLSTM with attention on RAVDESS):** 72% accuracy across multilingual inputs.
- **HRV:** reliable stress metrics when electrodes were correctly positioned.

The fused Stress Index, updated with less than **two seconds latency**, proved more reliable than any single modality alone. The investigator-facing dashboard displayed real-time overlays of emotion labels, stress timelines, and ECG traces, enhancing situational awareness during interrogations. These results confirm the feasibility of MBPA as an objective, multimodal support tool in forensic contexts.

### D. Incident Correlation and Pattern Identification

The fourth phase combined structured and unstructured data to predict criminal responsibility and link related cases. The Random Forest classifier achieved 82% balanced accuracy when categorizing outcomes as “Likely Criminal,” “Likely Victim,” or “Inconclusive.” Complementary risk scoring translated predictions into actionable categories (Low, Medium, High, Critical), supporting prioritization of victim protection. Additionally, semantic similarity analysis using Sentence-BERT embeddings achieved strong Top-3 accuracy in case matching, enabling effective linking of new incidents to historical patterns. All analytic bundles were processed in under 3 seconds, demonstrating that the system is capable of delivering real-time decision support without performance bottlenecks.

### E. Integrated System Performance and Discussion

The integration of the four phases delivered substantial value for criminal investigations. Data entry congestion was reduced, efficiency improved, and standardized digital records were established, even when source documents were fragmented or multilingual. The modular links added analytic depth structured extractions fed into interrogation

prompts, while multimodal behavioral cues informed questioning strategies. Importantly, transparency and contestability were built-in: every output was accompanied by relevance scores, confidence levels, and override options, ensuring investigators retained ultimate control.

Nevertheless, limitations remain. Poorly scanned documents and mixed-language inputs still reduce OCR accuracy, and bias risks persist due to imbalances in training datasets. Adoption challenges also include investigator readiness, the need for participatory design, and requirements for ongoing training and regulatory oversight.

The framework provides measurable improvements over conventional practices. It demonstrates the potential for accelerated digitization, improved interrogation support, multimodal stress monitoring, and explainable cross-case correlation, while preserving human-in-the-loop accountability. These results indicate that Lexa AI can serve as a foundational step toward transparent, ethical, and AI-augmented criminal investigation systems.

TABLE 1 RESULTS COMPARISON

Phase	Metric	Results	Processing Time
Automated Data Collection	Accuracy	83.51% (Gemini 2.0 Flash), 81.58% (GPT-4o); CER: 21.3% vs. 44.1%	5,049 ms vs. 11,903 ms
Dynamic Question Generation	Relevance	0-10 relevance scale; RL	Real-time, investigator override supported
Multimodal Analysis (FER)	Accuracy	63% (VGG-16, FER-2013)	Latency < 2 sec
Multimodal Analysis (SER)	Accuracy	72% (CNN-BiLSTM, RAVDESS)	Latency < 2 sec
Multimodal Analysis (HRV)	Reliability	Consistent if electrodes correctly positioned	Latency < 2 sec
Incident Correlation & Pattern Identification	Balanced	82% (Random Forest), Top-3 accuracy for case matching (Sentence-BERT)	< 3 sec per analytic bundle

## V. CONCLUSION

This study presented Lexa AI, an end-to-end AI-augmented criminal investigation platform that integrates four distinct modules: automated data collection, dynamic question generation, multimodal behavioral and physiological analysis, and incident correlation with predictive analytics. Together, these phases demonstrated how advanced techniques including large language models, reinforcement learning, multimodal fusion, and semantic similarity can transform conventional investigative practices into more efficient, accurate, and explainable workflows.

Evaluation confirmed that the system reliably digitizes multilingual legal documents, adapts interrogation strategies in real time, provides objective indicators of stress and credibility, and links new incidents with historical cases in under three seconds. These improvements address critical inefficiencies in current investigative processes by enhancing speed, transparency, and analytic depth while preserving investigator control. Despite these advancements, challenges remain. OCR accuracy declines on poorly scanned inputs, risks of algorithmic bias persist due to unbalanced training datasets, and full adoption will require integration with legacy systems, practitioner training, and regulatory oversight. Addressing these limitations is essential to ensure ethical, fair, and accountable deployment.

Lexa AI demonstrates the potential of state-of-the-art AI to augment human expertise in criminal investigations. By embedding transparency, contestability, and human-in-the-loop mechanisms, the platform offers a responsible pathway toward next-generation investigative systems—capable of supporting law enforcement with greater agility, fairness, and trustworthiness.

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