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Technologies in the Architecture of an AI-Driven Analytical Engine: Facilitating Real-time Police Surveillance

Prof Arup Barman[1] , Saswati Nath[2]

[1]Professor, Dept of Business Administration, Assam University, Silchar (India)

[2]Superintendent of Training, North East Police Academy, Meghalaya (India)

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ABSTRACT

In the age of artificial intelligence, real-time policing relies on high-level and diverse technologies. Generating data, decisions, responses, and surveillance strategies depends on efficient system generation. AI is critically important for real-time surveillance and policing, from data collection and analysis to decision execution. To implement AI technologies, data fusion and computing fusion occur at multiple points between data collection and response operations. The paper synthesises the empirical evidence of AI and related technologies used for real-time policing and surveillance. As real-time surveillance technologies are multifarious, multi-staged technologies are used in an AI-driven analytical engine that ranges from data collection to operational response; a clear mapping of the technology architecture is needed.

This paper attempts to identify technologies, synthesise the use, and design a robust technology mapping to complete the architecture of an AI-driven data analytical engine for enabling real-time surveillance intelligence. The paper synthesised and classified the technologies used in real-time AI-Driven Policing (RTAIDP), which could fill a strong gap in existing literature on real-time policing, even though AI policing literature is abundant.

Keywords: Real-time Policing, Data Fusion, Technology Fusion, Integrated intelligence, Analytical Engine, Technology Architecture

INTRODUCTION RTAIDP

Real-time police surveillance is the use of artificial intelligence (AI) to continuously monitor and analyse surveillance data to detect, assess, and respond, thereby supporting policing decisions [1], [2], [3]. AI-driven real-time policing is an integrated framework that combines a real-time data-capturing system, data analytics, artificial intelligence, automated decision support, and human oversight to detect, predict, prevent, and respond to criminal incidents [4], [5], [6], [7]. Data to Analysis (D_2A), Data to Response (D_2R), and Data to Strategy (D_2S) for real-time surveillance are to be accomplished through a critical process and systems. AI is mostly used between D_2A, D_2R, and D_2S, depending on the available system design. As applied systems for real-time policing begin with analysis, which is critical to understanding, system design detailing will enable the implementation of real-time policing surveillance.

AI-Driven Analytical Engine (ADAE) is the core of the proposed model, which synthesises AI analytics, data analytics platforms, inference engines, and decision-support systems [8]. The general definition of ADAE is an intelligent computational framework that integrates artificial intelligence, machine learning, data fusion, and real-time analytics to transform heterogeneous data into actionable insights for decision-making and operational response [9]. ADAE proposes a real shift from reactive policing to preventive policing through the deployment of continuous situational awareness and intelligent resource deployment [10]. The simple system-based expression of ADAE is -

$$\textbf{\textit{Police Effectivenes}} = f(AIc + DI + PA + DSS + RO + CL)$$

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Where,
AIc = AI capability,
DI= Data Integration,
PA=Predictive Analytics,
DSS = Decision Support System
RO = Response operation,
CL = Continuous Learning

The ADAE process flow is
Crime Data Collection→ (2) Data Integration→(3) *AI Analysis→*(4) *Threat Detection→*(5) *Risk Prediction→*(6) *Decision→*(6) *Police Deployment→* (7) *Incident Resolution→*(8) *Outcome Feedback→*(9) *Model Learning*
***#Source**: ChatGPT (Prompt used to create "Process Flow of ADAE")*

LITERATURE REVIEW

The AIDAE process flow map indicates the literature to be reviewed under the nine clusters. With the AIDAE model as a constant, we are reviewing the relevant literature to assess the significance of the AIDAE design and architecture for real-time police surveillance. Referring to the data acquisition layer, Choudhury (2016 [11]) revisited the video analytics pipeline for surveillance, focusing on video streaming but not on integrating multi-sourced police intelligence. Elharrouss et al. (2021) [12] reviewed video surveillance systems and proposed a video surveillance architecture. Though they studied specifically surveillance-centric architecture in general, not in police surveillance. Ardabili et al. 2023 designed an AI-enabled video surveillance system for public safety in a smart city, focusing on a limited operational policing architecture [13]. Verdejo, D. and Eunika Mercier-L, 2022, focused on the application of video intelligence and decision support for surveillance, where a missing unified AI-engine design was noted [14]. Karbalaie et al. (2022) focused on event-oriented surveillance videos as a solution for smart policing, noting limited integration with predictive policing [15]. Johans et al. (2024) focused on developing a system for suspicious behaviour detection as part of human activity surveillance, but not on the real-time police response framework [16]. Toshpulatov et al. (2026) contributed to edge-constrained video analytics, focusing on hardware optimisation issues. They failed to focus on the aspects of strategic policing layers [17]. Mandal et al. (2026) contributed to YOLO-based threat detection by focusing on weapon detection; however, they did not develop an integrated analytical architecture for real-time policing [18]. So far, the literature indicates that Perry et al. (2013) were the first to provide a framework for predictive policing, with a core focus on crime prediction systems and mechanisms. However, they did not focus on real-time surveillance analytics systems, even for design [19]. Kounadi, O., Ristea, A., Araujo, A., et al. (2020) contributed a review on spatial crime forecasting. Still, they failed to integrate live surveillance [20]. Helterlein, J. (2021), in 'epistemologies of predictive policing: mathematical social science, social physics and machine learning', presented a theoretically focused analysis of machine learning-based predictive policing. This work could not generate any operational architecture [21]. Brayne (2021) focused on the big-data policing ecosystem from a sociological perspective but did not develop any technical architecture for ADAE [22]. In 2026, Farber contributed a systematic review on AI policing to clarify the role of AI in criminal justice, without focusing on developing an integrated real-time framework [23]. Parsons & Torenvlied (2026) contributed to the governance-centric explanation of AI policing benefits and risks, but did not focus on the technical implementation model of AI [24]. Chiara Gallese (2026) attempted to provide limited operational guidelines on AI regulation and architectural guidance [25]. Konda (2019) contributed to detection-oriented, AI-powered surveillance analytics in the absence of an intelligence fusion layer [26]. There is evidence that the London Underground tested real-time AI surveillance tools to detect crime and weapons, using a computerised vision system [27]. Another noteworthy piece of evidence is the Jaipur Police's implementation of AI-based event-specific crowd monitoring. Still, their work does not claim the use of a predictive analytics engine [28].

Research Gap

The 50 literature studies archived in SCOPUS revealed that there are no existing studies that propose and validate a comprehensive AI-Driven analytical engine that simultaneously integrates the following-

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Table 1: Synthesised Research Gap

Research Gap	Technology and Tools
Multisource surveillance data	CCTV, Body Camera, IoT, IoB, Databases, social media
Real-Time Data Fusion	Data Ingestion, Data Integration, Sensor Fusion, Video Fusion, Spatial Fusion, Identity Fusion, Semantic Fusion, AI Fusion, Stream Analytics, Decision Fusion
Computer Fusion and Behavioural Data Analytics	Multi-Camera Fusion, Object Detection, Facial Recognition, Pose Estimation, Object Tracking, Activity Recognition, Scene Understanding, Multi-Model Video Fusion
Predictive policing and risk prioritisation	**Predictive Policing Techniques are**: Crime Hotspot Prediction, Spatio-Temporal Analysis, Time Series Forecasting, Machine Learning Prediction, Deep Learning Forecasting, Network-Based Prediction, Behavioural Prediction
	Risk Prioritisation Techniques are: Risk Scoring Model, Bayesian Risk Assessment, Multi-Criteria Decision Analysis, Threat Prioritisation Matrix, Explainable AI, Graph-Based Risk Analysis, Anomaly-Based Risk Detection, Fuzzy Logic Risk Assessment
Explainable AI	SHapley Additive exPlanations, Local Interpretable Model-Agnostic Explanations, Counterfactual Explanations, Feature Importance Analysis, Partial Dependence Plots, Individual Conditional Expectation, Decision Trees, Rule-Based Systems, Attention Visualisation
Automated Decision Support	AI Techniques of ADS: Random Forest, XGBoost, LightGBM, Bayesian Networks, LSTM- Sequential Event Prediction, Transformer Models, Graph Neural Networks (GNN), Reinforcement Learning, Explainable AI (SHAP, LIME)
Real-Time Police Operational Response [29]	Event-Driven Monitoring, Complex Event Processing (CEP), Automated Dispatch Algorithms, Optimisation Algorithms, Shortest Path Optimisation, Bayesian Networks, XGBoost, Multi-Object Tracking, Face Recognition, Crowd Analytics, Multi-Criteria Decision Analysis (MCDA), Decision Rules + AI Recommendation, Graph Analytics, Real-Time Information Exchange, GIS Intelligence, Mobile Command Systems, UAV Surveillance, Live Video Streaming, Crime Forecasting Models, SHAP, LIME, Integrated Dashboard Analytics

Source: Authors (From SCOPUS Database)

Synthesised research gaps from the existing literature indicate a significant need for research on ADAE to facilitate police surveillance.

Statement of the Problem

In a seminal work, creating an architecture that covers all dimensions may be a Herculean task. Though there are ample possibilities for defining an AI-Driven analytical engine (ADAE), from a surveillance perspective, it can be defined as an “intelligent analytical platform that integrates computer vision, behavioural analytics, and predictive models to support continuous monitoring and threat assessment” [30], [31], [32], [33]. An analytical engine for surveillance means ‘an intelligent computational platform that integrates multi-source data acquisition, computer vision, behavioural analytics, and deploys information fusion, predictive modelling and automated reasoning to continuously monitor, detect, and generate actionable intelligence for real-time decision-making ' [34] [35] [36] [37] [38]. The definitions speak to the criticality of multidimensional architecture and design for the proposed AI-Driven Analytical Engine (ADAE) for real-time surveillance. The technologies used in the architecture of the AI-driven analytical engine are extensive and warrant appreciation.

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Objectives of the Study

The main aim of the paper is to appreciate the technologies used in the architecture of ADAE, as stated in the paper's title. To achieve the analytical engine's architectural aim, the following objectives must be met. They are-

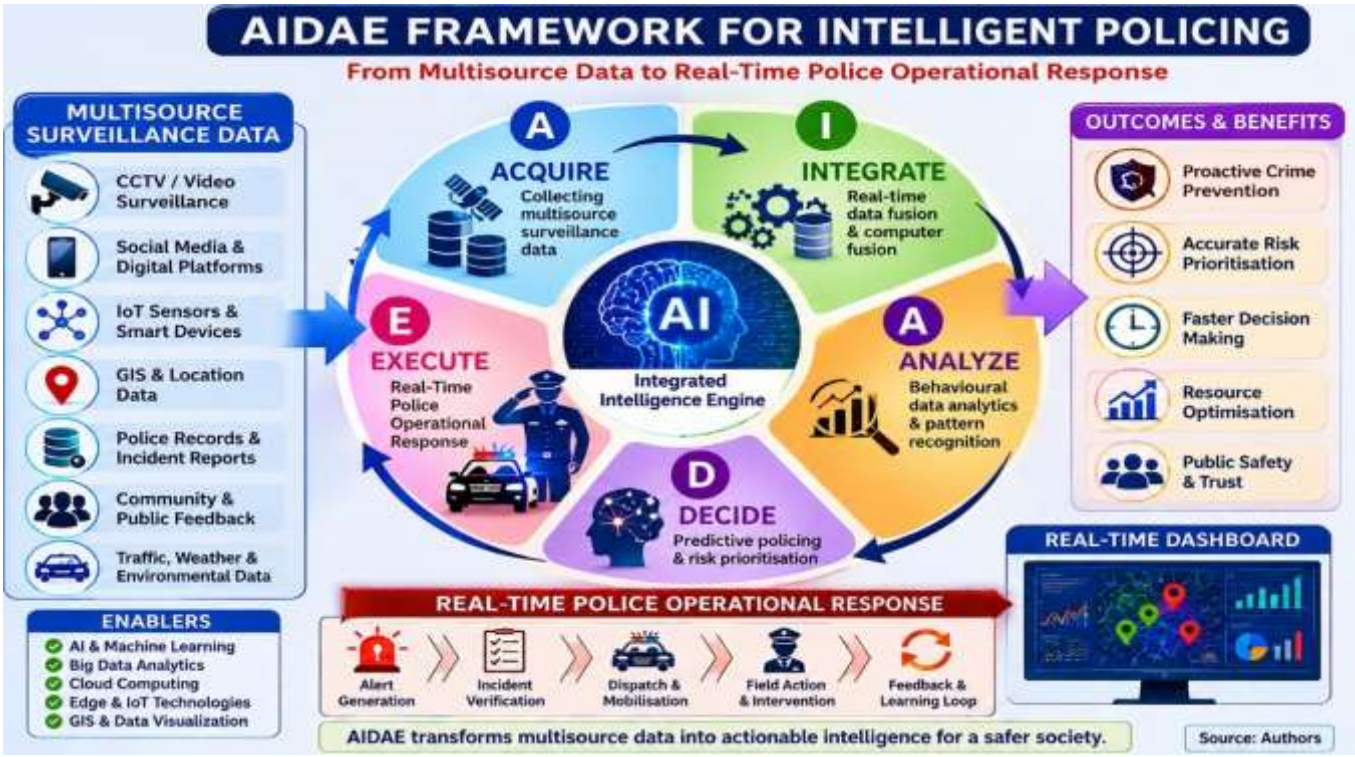
(i) To identify and cluster the available technologies for data acquisition & integration;
(ii) To appreciate the cluster of technologies used for AI Analytics & Intelligence;
(iii) To classify the technologies implemented for Risk Assessment & Prioritisation;
(iv) To gather the technologies used for Decision Support & Situational Awareness;
(v) Finally, to cluster technologies used for Police Response & Operational Effectiveness.

The identification and subsequent clustering of technologies would be contextualised for real-time surveillance in AI policing.

Design and Architecture of AIDAE

We began our approach to intelligent policing with the title "AI-Driven Analytical Engine (AIDAE)" to facilitate real-time policing. The core of intelligent policing starts with the activities of acquiring (A) the multi-source data for surveillance. Next, the acquired data needs to be integrated into the system so that it is ready for analysis. The integration of multi-sourced data in real time requires data fusion, which occurs on terminal computers and may be terminal or computer fusion. Figure 1 shows the location of A and I, which serve as input to the analysis (A).

Figure-1



In the analysis phase, behavioural data should be analysed, and patterns should be recognised using AI. After the analysis, the next step in predictive policing is analogous to risk prioritisation. Here lies the importance of human heuristics, but AI can often help choose the right course of action, i.e., make a decision (D). After the decision phase, the operational response is deployed, analogous to execution (E) of the action based on the requirement. The operational actions may include alert generation, incident verification, dispatch mobilisation, field action or intervention, and the feedback and learning loop.

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Data Acquisition

In the AIDAE framework, data acquisition is a fundamental activity that requires the deployment of diverse technologies. To get a clear picture of data acquisition, technology deployment, and evidence collected through a plethora of literature. For AI and real-time policing, the use of multi-source data [39] can be categorised as video surveillance data, aerial surveillance data, and various other categories, as listed in column 1 of Table 2.

Table-2 Technology used for Various Data Categories for Data Fusion

1. Data Category	2. Data Sources	3. Technology Usage (Examples)	4. Application in Real-Time Policing
Video Surveillance Data	CCTV Cameras	Smart CCTV, IP Cameras	Crime detection, suspect tracking [40]
Aerial Surveillance Data	Drones/UAVs	Police drones, aerial imaging	Crowd monitoring, border surveillance [41]
Body-Worn Camera Data	Officer Cameras	Body cameras, helmet cameras	Incident verification, accountability [42]
Vehicle Surveillance Data	Dash Cameras	Patrol vehicle cameras	Traffic enforcement, pursuit monitoring [43], [44], [45]
License Plate Data	ANPR/ALPR Systems	Vehicle registration capture	Vehicle tracking, stolen vehicle detection [46]
Facial Recognition Data	Face Recognition Systems	Suspect identification databases	Identification and watchlist matching [47]. [48]
Criminal Records Data	Police Databases	FIRs, arrest records, warrants	Background intelligence [49]
Incident Data	Police Reports	Crime reports, case diaries	Crime pattern analysis [50] [51] [52], [53]
Emergency Call Data	Call Centers	100/112 calls, dispatch logs	Incident prioritisation [54] [55] [56]
Dispatch Data	CAD Systems	Computer-Aided Dispatch records	Resource deployment [57] [58]
GPS and Location Data	Tracking Systems	Patrol vehicles, officer GPS	Real-time asset tracking [59] [60] [61]
Mobile Device Data	Smartphones	App-derived location data, device identifiers	Suspect movement analysis [62], [63]. [64] [65]
Telecommunication Data	CDR/IPDR	Call Detail Records, Internet Logs	Network and link analysis [66]. [67]
Social Media Data	OSINT Platforms	X, Facebook, YouTube, Instagram	Threat intelligence, event monitoring [68], [69], [70], [71]
Open-Source Intelligence (OSINT)	Public Sources	Blogs, forums, news portals	Situational awareness [72], [73], [74], [75]
Criminal Network Data	Association Records	Known associates, gangs	Network analysis [76], [77], [78], [79]
Biometric Data	Identity Systems	Fingerprints, iris scans, face templates	Identity verification [80], [81], [82]
Traffic Data	Smart Transportation Systems	Traffic sensors, congestion reports	Route optimisation [83], [84], [85], [86]
Geospatial Data	GIS Systems	Maps, crime hotspots	Location intelligence [87], [88], [89],

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			[90], [91], [92]
Environmental Data	IoT Sensors	Weather, air quality, noise sensors	Context-aware policing [93], [94]. [95], [96], [97], [98]
Gunshot Detection Data	Acoustic Sensors	ShotSpotter-type systems	Rapid firearms incident detection [99], [100], [101], [102]
Smart City Data	Urban Platforms	Safe City systems	Integrated urban surveillance [103], [104]. [105]. [106]
Border Security Data	Entry/Exit Systems	Immigration checkpoints	Border intelligence [107], [108], [109], [110]
Financial Intelligence Data	Banking Records	Suspicious transaction reports	Financial crime detection [111], [112], [113], [114], [115]
Vehicle Registration Data	Transport Databases	Registration records	Vehicle ownership verification [116], [117], [118], [119], [120]. [121]
Passport and Travel Data	Immigration Systems	Passenger travel history	Movement intelligence
Community Intelligence Data	Citizen Reporting Platforms	Complaints, tip lines	Community policing [122]. [123], [124], [125], [126], [127]
Crowdsourced Data	Public Submissions	Citizen apps, social reporting	Event detection [128]. [129], [130], [131]
Sensor Network Data	IoT Infrastructure	Motion, vibration, and occupancy sensors	Perimeter security [132], [133], [134]. [135].
Satellite and Remote Sensing Data	Earth Observation Systems	Satellite imagery	Large-area surveillance [136], [137], [138]
Cyber Surveillance Data	Security Systems	Network logs, cybersecurity alerts	Cybercrime monitoring [139], [140], [141]. [142], [143], [144]

Column 2 of Table 2 demonstrates the data sources with basic technology usage. Column 3 of Table 2 lists the specific technologies deployed for data capture, and column 4 explains the use of multi-source data for real-time policing.

Data Fusion Engine

All multi-sourced data is to be ingested into the system. Real-time streaming is the continuous ingestion, transformation, cleansing, standardisation, and delivery of data generated for immediate analysis [145]. Real-time streaming supports AI-based inference, monitoring, and decision-making [146]. Common technologies for data ingestion include Apache Kafka, Amazon Kinesis, and Google Pub/Sub, while stream processing technologies include Apache Flink, Apache Spark Structured Streaming, and Apache Storm [147]. Data normalisation is implemented through API-led integration and a connector framework that extracts heterogeneous data from multiple sources and transforms it into a canonical schema for analysis [148], [149]. Representative technologies for API-led integration include MuleSoft Anypoint Platform, Apache Camel, Airbyte, dbt, and Apache Airflow, which collectively support API connectivity, schema mapping, data transformation, workflow orchestration, and enterprise integration patterns [150]. In data ingestion, batch import means collecting and processing data periodically rather than processing each record as it arrives [152],[151]. IoT and sensor data are commonly used as real-time policing data sources for ingestion. Both devices continuously generate real-time data through communication protocols such as MQTT, CoAP, HTTP, and OPC UA to edge, fog, or cloud platforms for storage, processing, and analytics [153]. The ingested data are processed and normalised through data cleaning, normalisation, deduplication, entity resolution, geotagging, time synchronisation, and format standardisation to fit the data fusion engine [154].

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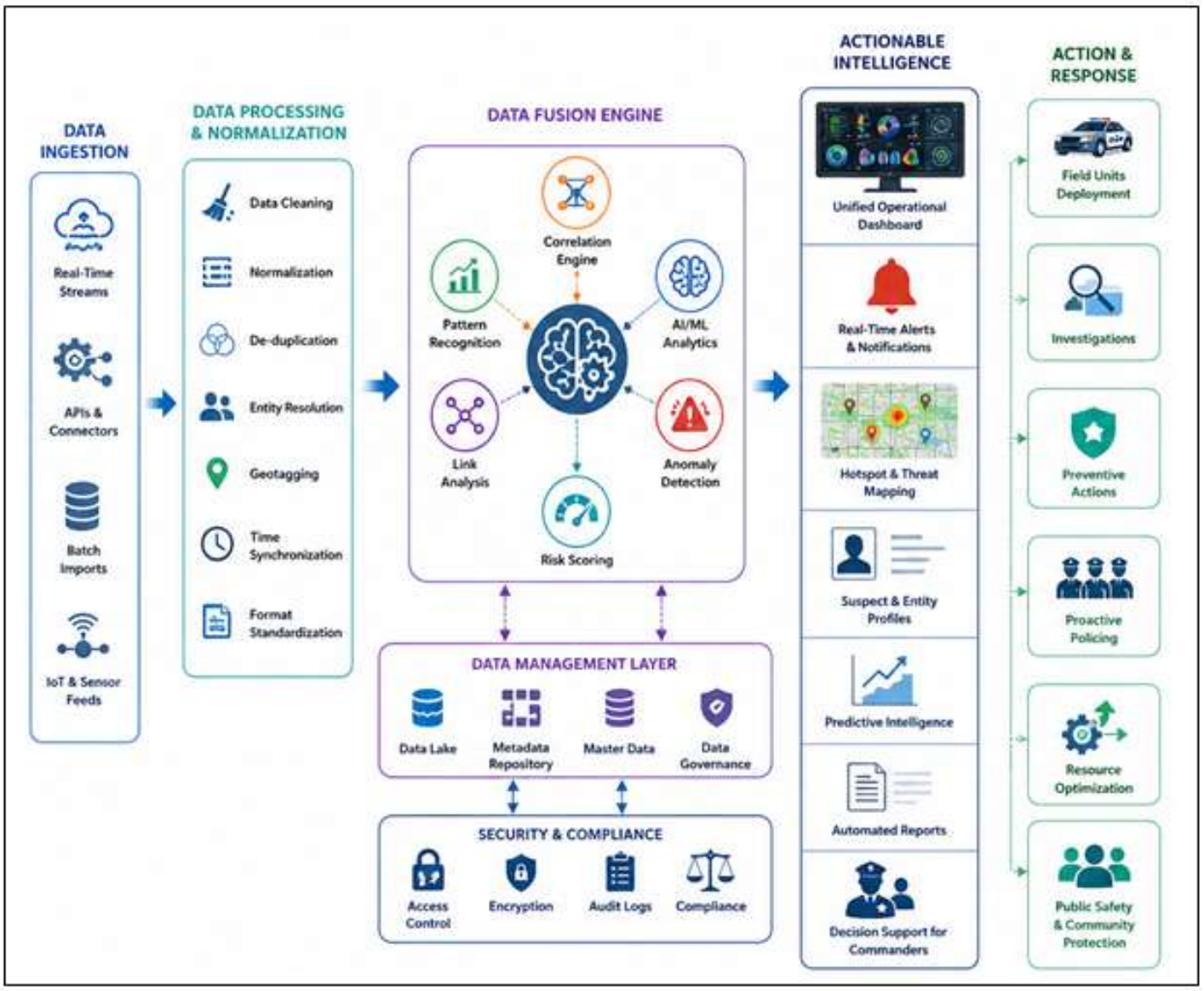
A data fusion engine is typically understood as a software or computational framework that integrates, correlates, and synthesises heterogeneous data sources to produce unified, consistent processed data for analysis. The data fusion process resolves inconsistencies and redundancies to generate high-quality information, thereby enabling artificial intelligence and decision support [155]. The data fusion engine includes a correlation engine, AI- and ML-based analytics, anomaly detection, a risk-scoring framework, a link-analysis framework, integrated software, and pattern recognition, as demonstrated in Figure 2. The efficiency of the data fusion engine depends on the efficiency of data management at different layers, as well as on enabling data security management at each layer, as described in the figure.

Figure 2: Data Fusion Engine Enabling Actionable Intelligence and Real-Time Response



Source: Author's Prompt in ChatGPT

Computational Fusion at Different Layers

The layers of data ingestion determine the computational fusion. The term "computational fusion" is a substitute for computational intelligence, information fusion, computational intelligence for information fusion, "multisource information fusion," and "multimodal data fusion" [156]. Figure 3 shows that computational fusion in the AIDAE framework is used to acquire multi-sourced behavioural data and to model baseline behaviour from historical data. The real-time computational fusion needs to be deployed at the level of real intelligence analysis to track behaviour in real time, analyse, and understand deviation scoring. Real-time computational fusion using AI at the decisional level (D), leveraging machine learning to detect

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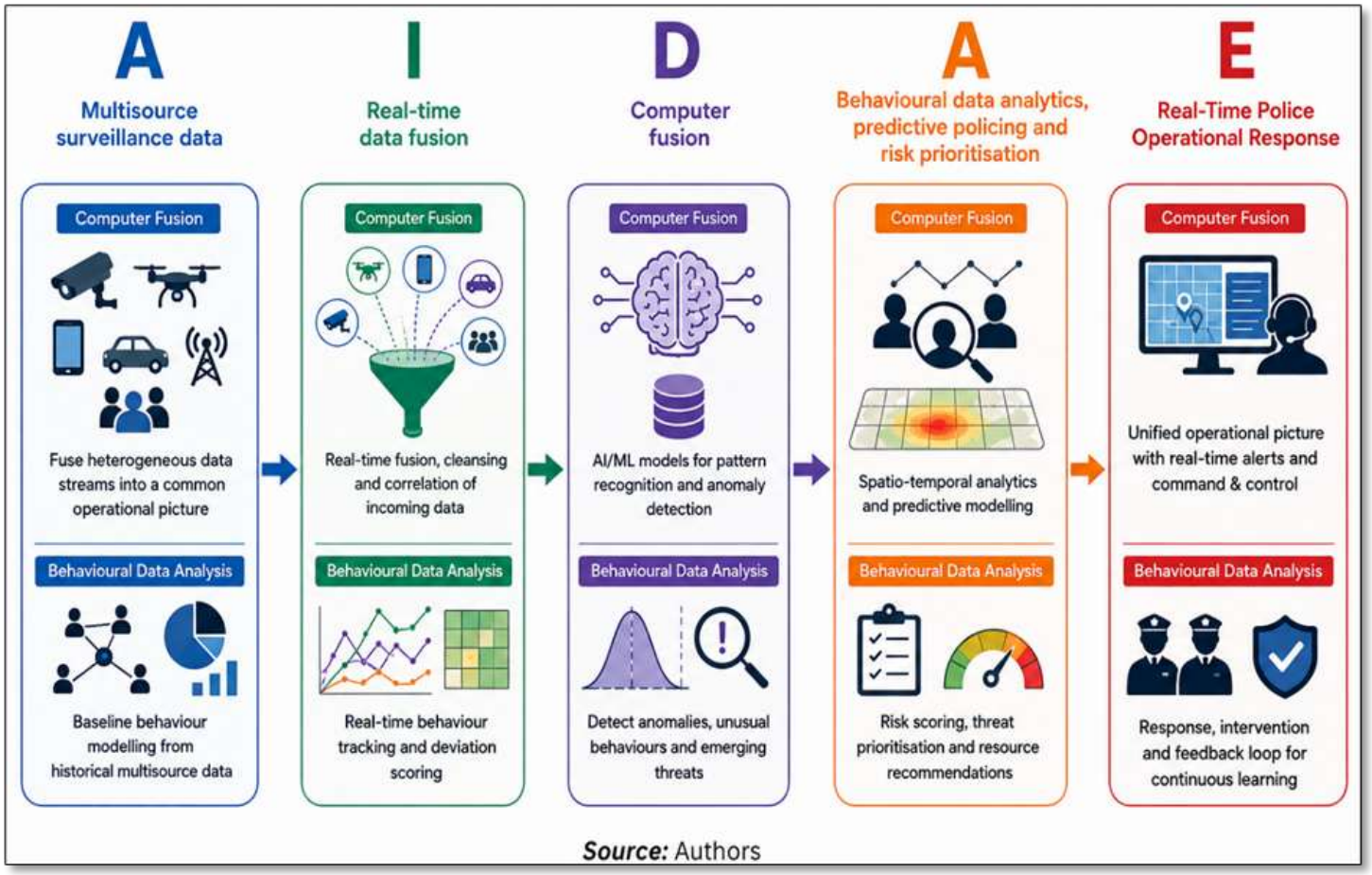
anomalies, unusual behaviour, and emerging threats for surveillance. At the level of behavioural data analytics for predictive policing, spatio-temporal analytics, aided by predictive modelling, enables risk scoring, threat prioritisation, and consequent resource recommendations. In an AI-driven analytical engine (ADAE), at the execution level, computational fusion is deployed to ensure a unified operational picture with real-time alerts, commands, and control. Here lies the end and beginning of real-time police operational action through the police response, intervention, feedback loop and continuous learning.

Figure 3, Computational Fusions at AIDAE



AI Application Layer in Real-Time Intelligence

Computational fusions occur across different layers to support multi-sourced data and multi-level analytics, and at the consequent response level of an AI-driven policing system. The conceptual configuration of an integrated intelligence engine is essential for the utilisation of AI models within the AIDAE framework. Figure 4 provides an exhaustive description of the integrated intelligence engine and the use of AI models across different layers with distinct objectives. In designing an integrated intelligence in support of an integrated analytical engine, language and understanding, AI models are in use. Language-level AI models are natural language processing models that can be deployed to recognise intents and extract entities. Semantic search and knowledge graph embedding are enabled by the application of knowledge-level AI that needs to be integrated in real-time surveillance. Thus, AI models for real-time surveillance and policing; reasoning and planning models; multi-model, predictive, and analytical models; personalisation and recommendation models; agent and action models; safety and trust models; and many domain-specific models. AI today can become an essential part of real-time surveillance, where multi-source data is the core.

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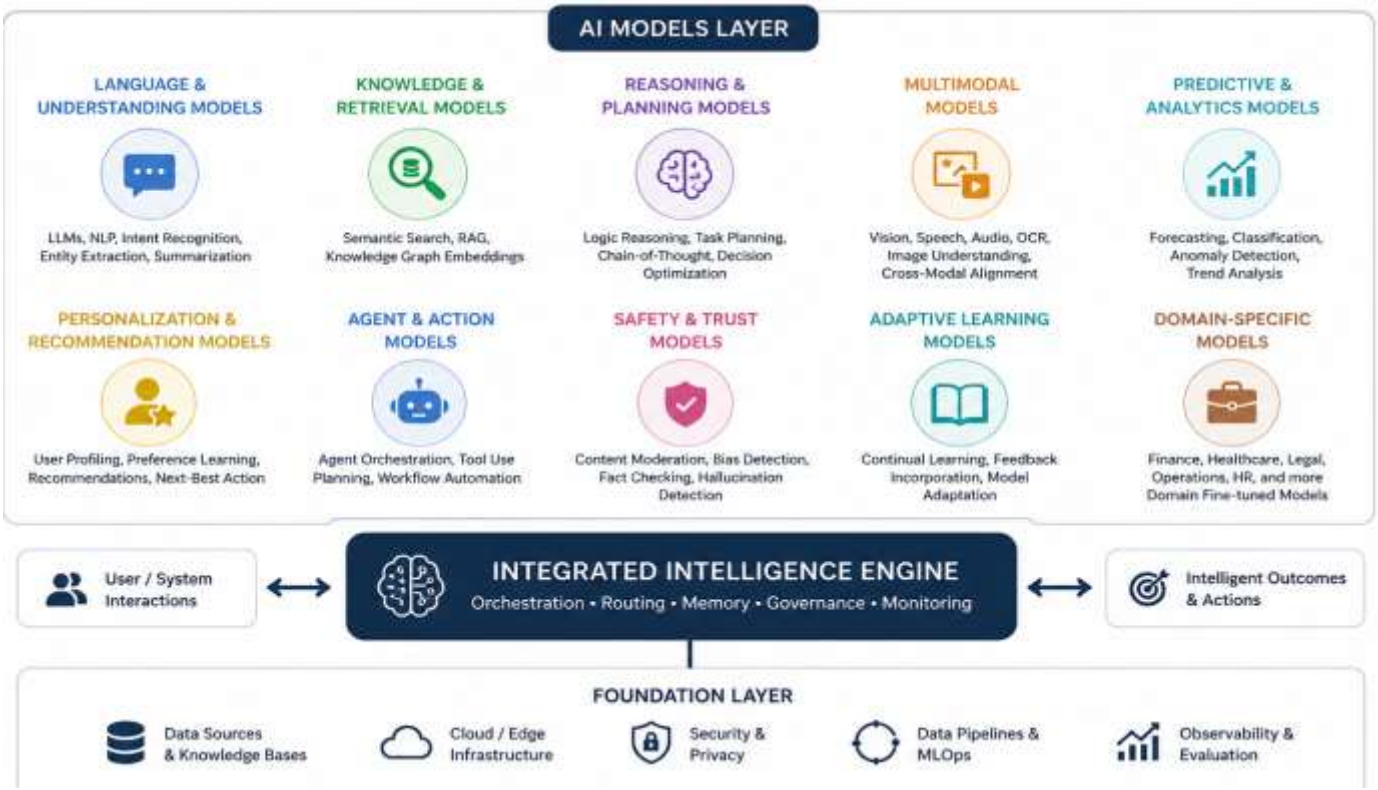
Figure 4, Integrated Intelligence Engine



Technologies for Risk Assessment

Technologies used in AI-enabled risk assessment and prioritisation may be classified into interconnected domains [157]. Based on the systematic risk assessment framework, AI-based risk assessment comprises multiple dimensions of technology [158]. The following classification of technologies for predictive or smart policing, aligned with the AIDAE framework, is synthesised in Table 4 from the literature.

Table 4, Technologies for Risk Assessment and Prioritisation

Technology Categories	Typical AI Techniques	Representative Application	Key Reference Sources
Machine Learning	Random Forest, Decision Trees, Support Vector Machines, Gradient Boosting, Neural Networks	Recidivism prediction, offender prioritisation, patrol allocation	[159], [160],
Predictive Analytics	Statistical learning, regression, Bayesian prediction	Crime hotspot prediction, burglary forecasting	[161], [162], [163]
Geographic Information Systems (GIS) & Spatial Analytics	Spatial statistics, kernel density estimation, hotspot analysis	Crime mapping, patrol optimisation	[164] ,[165], [166]
Big Data Analytics	Distributed analytics, feature engineering	Multi-source intelligence fusion, operational dashboards	[167], [168],[169]
Natural Language Processing (NLP)	Named Entity Recognition, Topic	Incident classification, intelligence extraction	[170], [171]

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	Modelling, Large Language Models		
Computer Vision	Deep CNNs, Object Detection, Facial Recognition	CCTV monitoring, suspect identification, anomaly detection	[172], [173]
Decision Support Systems (DSS)	Rule-based AI, Expert Systems, Hybrid AI	Officer deployment, threat ranking, case prioritisation	[174]. [175]
Risk Scoring Algorithms	Ensemble Learning, Probability Models	Harm Assessment Risk Tool (HART), recidivism prediction	[176], [177]
Explainable AI (XAI)	SHAP, LIME, interpretable ML	Explainable risk predictions, auditability	[178], [179]
Data Fusion & Intelligence Fusion	Data integration, entity resolution, knowledge fusion	Multi-agency intelligence prioritisation	[180], [181]
Ethical AI & Governance Technologies	Bias detection, fairness metrics, impact assessment	Bias detection, fairness metrics, impact assessment	[182], [183]

Technologies used for Police Response & Operational Effectiveness

In operational response, the police or surveillance professionals need to deploy multiple technologies. In policing and law enforcement technology research, landmark literature indicates that the common use of technologies for operational purposes is summarised in Table 5.

Table 5, Technologies usage for Police Response & Operational Effectiveness

Sources/Literature	**Referred Technologies**	**Nature of Tech**	**Purpose and Usage**
[184] [185], [186]	Computer-Aided Dispatch (CAD)*	Integration with 911, GPS/AVL, Mobile Data Terminals, GIS, and police databases.	Quick Emergency Response, Surveillance Resource Allocation, Dispatch Optimisation
[87] [88], [89], [90], [91], [92]	GIS	Integrated Technology	Crime mapping, hotspot analysis, patrol deployment
[59] [60], [61]	GPS & Automatic Vehicle Location (AVL)	Integrated Technology	Real-time patrol tracking, shortest route selection
[43], [44], [45]	Body-Worn Cameras (BWC)	Integrated Data Collection Tech	Evidence collection, accountability, and officer safety
[187], [3], [9], [19], [25]	Predictive Policing Systems	Integrated Tech to AI	Crime forecasting, hotspot prediction
[188] [7], [41]	Drones (UAVs)	Integrated into Data Systems and AI	Surveillance, disaster response, search and rescue
[189] [190] [191], [192] [184], [47]	Facial Recognition Systems	Integrated System into AI	Suspect identification
[46], [116], [117], [121]	Automatic Number Plate Recognition (ANPR/LPR)	Integrate Data and AI	Vehicle tracking, stolen vehicle detection

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[40], [172], [173]	CCTV & Smart Surveillance	Integrate into Data and AI	Real-time monitoring, crime deterrence
[184] [185], [186]	Mobile Data Terminals (MDTs)	Integrated into Data and AI	Field information access
[193]	Digital Evidence Management Systems (DEMS)	Integrated into Data and AI	Secure evidence storage and retrieval
[194] [195]	Social Media Intelligence (SOCMINT)	Multi-Source Intelligence integration	Public intelligence gathering, crisis monitoring
[196], [197], [198]	Real-Time Crime Centres (RTCC)	Multi-source intelligence integration	Improve investigative outcomes by integrating surveillance technologies, crime databases, and operational intelligence.
[93], [94]. [95], [96], [97], [98][132], [133], [134]. [135].	IoT Sensors & Smart City Platforms	Multi-Source Intelligence and Data Collection	Automated incident detection

The study proclaims that AI is a common technology in the paper.

Considering the complexity of understanding the usage of CAD* in Table 5 in police response and operational effectiveness, the following points may clarify utilities:

(i) Facilitate reducing police emergency response time.

(ii) Enable faster call prioritisation and incident classification.

(iii) Facilitate improving allocation and deployment of patrol units.

(iv) Helps in real-time situational awareness for dispatchers.

(v) Works through an integration with 911, GPS/AVL, Mobile Data Terminals, GIS, and police databases.

(vi) CAD enhances coordination among police, fire, and emergency medical services.

(vii) Facilitates better workload balancing and resource utilisation.

(viii) Helps in improved officer safety through timely information sharing.

(ix) CAD helps in increasing accountability through digital logging and performance analytics.

(x) Finally, CAD supports data-driven policing, hotspot analysis, and community policing initiatives.

DISCUSSION

The findings demonstrate that the proposed AI-Driven Analytical Engine (ADAE) extends the current body of knowledge by integrating technologies that have largely been investigated in isolation. Earlier studies primarily concentrated on specific components such as video surveillance, predictive policing, computer vision, or decision support rather than presenting a unified analytical architecture for real-time policing (Choudhary & Chaudhury, 2016 [11]; Elharrouss et al., 2021 [12]; Ardabili et al., 2023 [13]; Perry et al., 2013 [19]). The proposed architecture addresses this gap by combining multi-source data acquisition, real-time data fusion, AI analytics, behavioural intelligence, predictive risk assessment, explainable AI, automated decision

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support, and operational response within a single framework. This integrated perspective is consistent with recent evidence that effective AI-enabled policing depends on the convergence of heterogeneous data sources, intelligent analytics, and coordinated operational systems rather than on isolated technologies (Afzal & Panagiotopoulos, 2025 [39]; Lee et al., 2024 [29]; Farber, 2026 [23]).

The architecture further highlights that operational effectiveness depends not only on AI algorithms but also on the quality of data integration and continuous learning. Technologies such as Apache Kafka, stream processing, API-led integration, GIS, CAD, body-worn cameras, drones, facial recognition, RTCCs, and IoT platforms collectively create a continuous intelligence cycle that transforms raw surveillance data into actionable policing decisions (Akidau et al., 2018 [147]; Kleppmann, 2017 [151]; Davies & Krame, 2023 [7]; Camello et al., 2025 [6]). The inclusion of explainable AI, governance mechanisms, and human oversight also addresses growing concerns about transparency, fairness, accountability, and the ethical deployment of AI in law enforcement (Gallese, 2026 [25]; Parsons & Torenvlied, 2026 [24]). Therefore, the proposed ADAE provides a comprehensive conceptual architecture to guide future empirical validation, system development, and policy implementation for intelligent real-time police surveillance.

CONCLUSION

This study identified, synthesised, and classified the technologies required for designing an AI-Driven Analytical Engine (ADAE) capable of supporting real-time police surveillance. The proposed architecture demonstrates that intelligent policing requires the seamless integration of multi-source data acquisition, computational data fusion, AI-based behavioural analytics, predictive risk assessment, explainable decision support, and technology-enabled operational response within a continuous learning ecosystem. By consolidating fragmented technological advances reported in previous studies into a unified architectural framework, the paper offers a practical conceptual blueprint for developing next-generation real-time policing systems. Beyond its theoretical contribution, the framework guides researchers, police organisations, system architects, and policymakers seeking to design scalable, interoperable, and ethically responsible AI-enabled surveillance platforms. Future research should empirically validate the proposed architecture through prototype implementation, performance evaluation, explainability assessment, privacy-preserving mechanisms, and real-world operational testing across diverse policing environments.

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