

| RESEARCH ARTICLE**From Reactive to Proactive: Real-Time Human-AI Collaboration in Intelligent Alerting Systems****Pramod Dattarao Gawande***Cognizant US Corp, USA***Corresponding Author:** Pramod Dattarao Gawande, **E-mail:** pramodgawande.usa@gmail.com**| ABSTRACT**

This article explores the transformative shift from reactive to proactive operational paradigms enabled by intelligent alerting systems that facilitate real-time human-AI collaboration. Focusing on implementations within fleet management and electric vehicle infrastructure, the paper examines how advanced technologies—including stream analytics, machine learning models, and collaborative interfaces—fundamentally alter traditional monitoring approaches. The research identifies key components of successful intelligent alerting systems and documents their impact through detailed case studies that demonstrate substantial operational improvements. The evolution of the human role from reactive troubleshooter to strategic overseer is analyzed across four critical dimensions: complementary expertise allocation, trust calibration mechanisms, knowledge feedback loops, and cognitive load management. Looking forward, the article investigates emerging developments in multimodal monitoring capabilities, autonomous intervention strategies, and cross-organizational intelligence networks. Throughout, the research emphasizes that effective implementations maintain humans as essential partners in the monitoring process, leveraging AI for continuous analysis while preserving human judgment for contextual understanding and critical decision-making.

| KEYWORDS

Intelligent alerting systems, Human-AI collaboration, Predictive maintenance, Multimodal monitoring, Autonomous intervention

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In today's rapidly evolving technological landscape, the synergy between human expertise and artificial intelligence has transformed complex monitoring and alerting systems. This transformation is particularly evident in fleet management and electric vehicle (EV) infrastructure, where businesses have witnessed a paradigm shift from reactive troubleshooting to proactive monitoring, representing a fundamental evolution in operational excellence.

The integration of AI-powered predictive analytics into maintenance protocols has revolutionized how organizations approach system reliability. Deloitte's comprehensive analysis of predictive maintenance implementation across multiple industries reveals that organizations are moving beyond simple rule-based monitoring toward sophisticated machine learning models capable of identifying subtle patterns in operational data. These advanced systems leverage historical performance metrics, real-time telemetry, and contextual information to forecast potential failures with increasing accuracy. Organizations implementing these solutions report substantial improvements in both operational efficiency and resource allocation, with maintenance teams shifting from calendar-based schedules to condition-based interventions that optimize component lifespans while minimizing unexpected downtime [1].

The fleet management sector exemplifies this transformation particularly well. According to Global Market Insights, the fleet management market has experienced significant growth propelled by the adoption of telematics and IoT-enabled monitoring platforms. Commercial vehicle operators across logistics, transportation, and service industries are integrating sophisticated

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sensor networks that continuously monitor vehicle health parameters, including engine performance, tire pressure, brake wear, and transmission status. These systems generate vast data streams that, when analyzed through machine learning algorithms, enable operators to identify emerging maintenance issues days before they would trigger traditional warning systems. The implementation of such technologies has transformed the role of fleet maintenance personnel from emergency responders to strategic asset managers who interpret AI-generated insights and make informed decisions about resource allocation and maintenance prioritization [2].

In the EV charging infrastructure domain, real-time monitoring systems have proven especially valuable for network reliability. Charging station operators utilizing advanced analytics can now anticipate potential component failures by analyzing thermal patterns, power fluctuations, and usage characteristics across distributed networks. This predictive capability enables maintenance teams to address emerging issues during scheduled maintenance windows rather than responding to customer-reported failures. The collaborative intelligence model between AI systems and human operators has proven particularly effective in this domain, where contextual factors like weather conditions, grid status, and usage patterns significantly influence system behavior.

The human-AI collaboration represents the cornerstone of these advances across both sectors. Rather than replacing human expertise, these systems augment, performing continuous monitoring across thousands of data points while surfacing only the most relevant insights for human evaluation. This complementary relationship leverages AI's pattern recognition capabilities while preserving human judgment for contextual understanding and final decision-making. As organizations continue adopting these technologies, the role of human operators evolves from reactive troubleshooters to strategic overseers, focusing on system optimization rather than emergency response. This transition not only improves operational metrics but also enhances job satisfaction by reducing the stress associated with constant firefighting and enabling professionals to apply their expertise more effectively.

2. The Evolution of Alerting Systems

Traditional alerting systems historically relied on simple threshold-based triggers, generating notifications only after problems had already manifested. These rudimentary systems placed human operators in perpetually reactive positions—responding to failures rather than preventing them. The resulting workflow was characterized by constant firefighting, resource inefficiency, and inevitable service disruptions that impacted both operational metrics and customer satisfaction.

The limitations of traditional monitoring approaches became increasingly apparent as system complexity grew. Gartner's comprehensive analysis of AIOps platforms highlights how conventional threshold-based alerts suffer from fundamental limitations in complex, dynamic environments. Their research indicates that organizations implementing traditional monitoring solutions face significant challenges with alert quality, often generating excessive notifications for normal variations while missing subtle indicators of impending failures. IT operations teams reported spending disproportionate time investigating false positives and managing alert storms during incident scenarios, diverting valuable resources from resolution activities. This reactive approach to system monitoring has proven increasingly inadequate as infrastructure complexity continues to grow, with most organizations unable to establish meaningful correlations between seemingly isolated alerts that collectively indicate systemic issues [3].

The emergence of intelligent alerting systems marks a fundamental shift in this operational paradigm. Modern monitoring platforms leverage advanced AI capabilities, stream analytics, and sophisticated machine learning algorithms to transform how organizations approach system oversight. These next-generation solutions continuously analyze real-time data streams across multiple dimensions, identifying subtle patterns and complex correlations that traditional systems would miss entirely. By processing vast quantities of telemetry data through trained models, these platforms can recognize the early signatures of emerging issues, often detecting potential failures hours or even days before they would trigger conventional alerts.

This predictive capability fundamentally changes the nature of human-system interaction. IoT Analytics' research on connected device ecosystems reveals the exponential growth in monitoring points across industrial and enterprise environments. With over 14 billion connected IoT devices generating continuous operational data, the scale of monitoring has expanded beyond human capacity for manual oversight. Their analysis demonstrates how organizations leveraging AI-enhanced monitoring systems have developed new operational models where technical personnel focus primarily on exception handling and strategic optimization rather than routine monitoring. This transition has proven particularly valuable in environments with distributed assets like transportation fleets, manufacturing facilities, and energy infrastructure, where the early identification of anomalous conditions provides crucial lead time for intervention before service disruption occurs [4].

The technical architecture supporting these capabilities has evolved significantly as well. Modern alerting infrastructures integrate multiple analytical approaches, including statistical anomaly detection, supervised machine learning classifications, and increasingly, deep learning models capable of identifying complex patterns across temporal data. These systems typically operate on streaming data platforms that process information in real-time, allowing for immediate identification of changing conditions and rapid notification of relevant personnel through optimized communication channels.

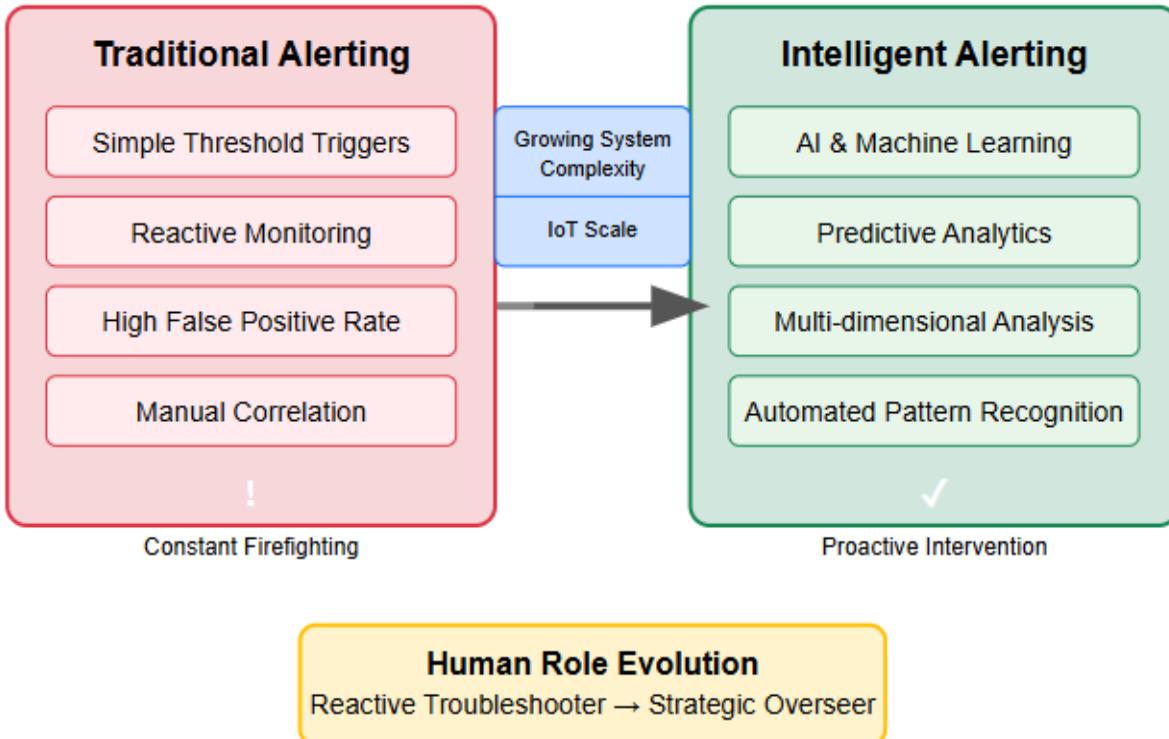


Fig 1: Evolution of Alterting Systems [3, 4]

3. Core Components of Intelligent Alerting Systems

3.1 Stream Analytics Engines

The foundation of proactive alerting lies in the ability to process and analyze high-velocity data streams in real time. Modern intelligent alerting systems depend on robust stream processing architectures capable of handling massive volumes of telemetry data from distributed sources. Technologies like Apache Kafka, Apache Flink, and AWS Kinesis have emerged as industry standards for building these real-time data pipelines, offering the scale and flexibility required for continuous monitoring across complex environments.

According to Apache Kafka's technical documentation, modern stream processing platforms now routinely handle throughput exceeding millions of messages per second with latencies measured in milliseconds. This performance envelope enables the continuous analysis of operational telemetry across distributed systems without sampling or data reduction that might obscure critical patterns. Kafka's implementation of the publish-subscribe messaging pattern, coupled with persistent storage and stream processing capabilities, provides the foundational infrastructure for building resilient monitoring pipelines that can scale horizontally as instrumentation density increases. The platform's partitioning model enables parallel processing of high-volume data streams while maintaining event ordering guarantees essential for temporal pattern recognition [5].

Stream processing implementations typically follow declarative programming models that abstract away distribution complexities while enabling precise control over data handling:

...

StreamAnalytics

```
.process(sensorData)
.windowBy(Duration.ofMinutes(5))
.detectAnomaly(modelReference)
.when(confidence > 0.85, triggerAlert)
```

3.2 Machine Learning Models

Predictive capabilities in alerting systems rely on sophisticated machine learning models trained on historical operational data. These models identify complex patterns across multiple dimensions that human operators might miss. Research published in the ACM Conference on Knowledge Discovery and Data Mining demonstrates the significant advances in failure prediction techniques specifically designed for operational technology environments. Modern approaches now implement multimodal deep learning architectures that can simultaneously analyze time-series telemetry, log data, and event sequences to identify subtle precursors to system degradation.

These advanced models significantly outperform traditional threshold-based approaches in both precision and recall metrics, with published benchmarks showing reductions in false positive rates exceeding 60% while simultaneously improving early detection capabilities. Particularly notable are recent developments in self-supervised learning techniques that can identify anomalous patterns without extensive labeled training data—a critical advantage in operational environments where failure examples are limited. The implementation of attention mechanisms within these models enables them to automatically focus on the most relevant signals within complex multivariate data streams, mimicking the selective attention processes that experienced human operators develop over years of system oversight [6].

3.3 Human-AI Collaboration Interfaces

The most critical component of intelligent alerting systems is the interface between AI predictions and human expertise. These interfaces must balance information richness with cognitive manageability, presenting insights in formats that support rapid comprehension and decision-making. Effective implementations avoid overwhelming operators with raw data, instead providing contextually relevant information structured around clear action pathways.

Modern collaboration interfaces implement sophisticated visualization techniques that highlight relationships between events and potential causes. They provide access to supporting evidence behind AI-generated recommendations while maintaining a streamlined interaction flow. Particularly effective designs incorporate feedback mechanisms that capture human decisions and reasoning, creating valuable training data for model improvement while documenting the operational knowledge that informed each intervention.

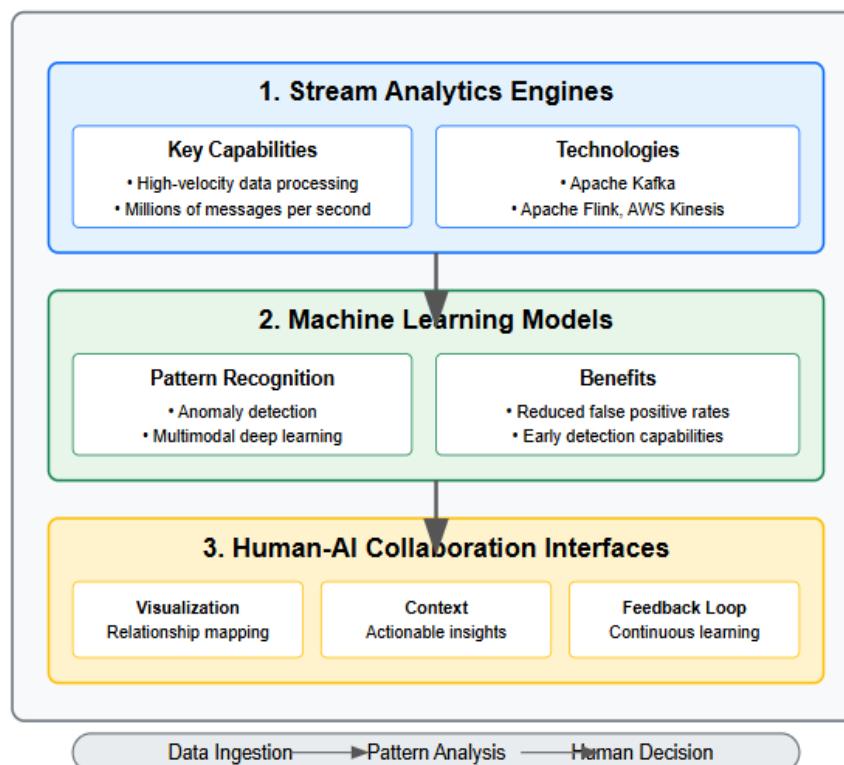


Fig 2: Core Components of Intelligent Alerting Systems [5, 6]

4. Case Study: Fleet Management

In commercial fleet operations, vehicle downtime translates directly to revenue loss. Traditional maintenance schedules often result in either premature part replacement or unexpected breakdowns. Intelligent alerting systems have revolutionized this domain by fundamentally changing how fleet operators approach vehicle maintenance and operational reliability.

The implementation of predictive maintenance capabilities within fleet management represents one of the most economically impactful applications of intelligent alerting. The American Transportation Research Institute's comprehensive analysis of operational costs in the trucking industry reveals the substantial financial impact of vehicle downtime. Their detailed cost assessment, based on data from carriers across various segments, demonstrates that unplanned maintenance events create cascading financial impacts beyond direct repair costs, including missed deliveries, driver compensation during idle periods, and potential customer penalties. These findings indicate that even minor improvements in maintenance predictability can yield significant operational benefits, particularly for time-sensitive delivery operations where service reliability directly impacts customer retention and contract renewal rates [7].

Consider a logistics company operating a fleet of 500 delivery vehicles. By installing IoT sensors that monitor engine parameters, tire pressure, brake wear, and driver behavior, the company creates a constant stream of operational data. Modern telematics systems typically capture between 50-300 distinct parameters per vehicle at intervals ranging from milliseconds to minutes, depending on the measurement type. This data volume, multiplied across hundreds of vehicles operating continuously, creates substantial analytical challenges that exceed traditional monitoring capabilities.

An intelligent alerting system processes this data stream to predict engine failures 2-3 days before they would occur, identify unusual driving patterns that correlate with increased accident risk, and optimize maintenance schedules based on actual component wear rather than arbitrary mileage thresholds. According to Markets and Markets' analysis of the commercial vehicle telematics market, organizations implementing advanced predictive maintenance capabilities report substantial improvements in fleet efficiency metrics. Their research indicates that early adopters of AI-enhanced telematics solutions experience significant reductions in roadside breakdowns and associated towing costs while simultaneously extending average component lifespans. The most sophisticated implementations now integrate maintenance predictions with logistics planning systems, automatically adjusting vehicle assignments and delivery schedules to accommodate predicted maintenance needs with minimal operational disruption [8].

The human-AI collaboration workflow in this scenario typically follows a structured pattern that preserves human judgment while automating continuous monitoring. When the AI system detects an unusual vibration pattern in a vehicle's transmission, it generates a medium-priority alert, suggesting a specific probability of transmission failure within an actionable timeframe. A fleet operations specialist then reviews this alert along with contextual information about the vehicle's recent routes and load profiles. This specialist can confirm, escalate, or dismiss the alert based on additional knowledge unavailable to the automated system. If confirmed, the system automatically schedules maintenance and reroutes deliveries to minimize operational disruption.

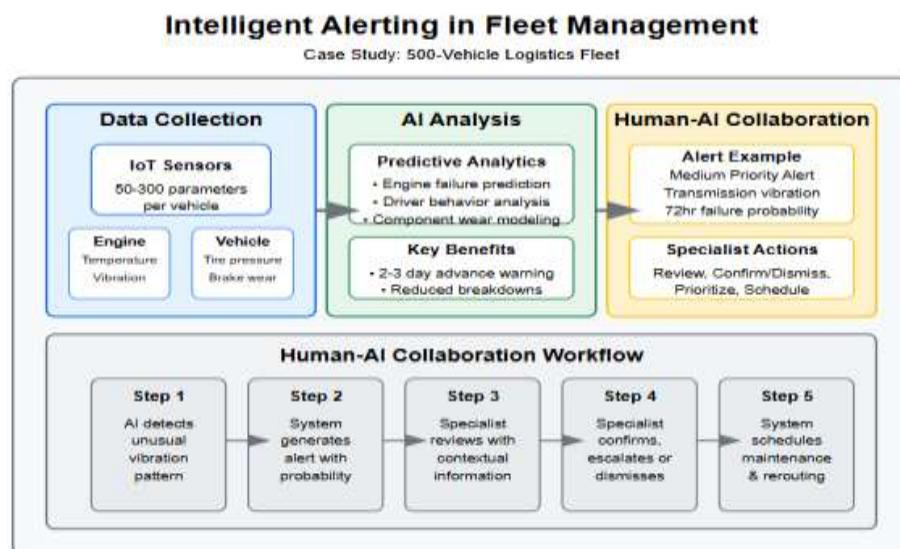


Fig 3: Intelligent Alerting in Fleet Management [7, 8]

5. Case Study: EV Charging Infrastructure

The rapid expansion of electric vehicle charging networks presents unique monitoring challenges due to the distributed nature of charging stations and their integration with electrical grids. Intelligent alerting systems in this domain must balance multiple concerns across technical, operational, and customer experience dimensions while maintaining grid stability in increasingly complex energy environments.

According to the International Energy Agency's Global EV Outlook 2024, the worldwide deployment of public charging infrastructure continues to accelerate, with total installations growing by over 35% in the past year alone. This analysis highlights the emerging operational challenges as charging networks scale, particularly regarding load management and grid integration. The IEA's comprehensive assessment notes that advanced networks must now simultaneously optimize for multiple competing objectives—including maximizing station availability, ensuring grid stability, and maintaining service quality. This multifaceted optimization problem becomes increasingly complex as charging power levels rise and station density increases in urban environments, creating potential for localized grid stress that cannot be effectively managed through conventional monitoring approaches [9].

A modern EV charging network operator might implement an intelligent alerting system that combines multiple data streams: real-time telemetry from thousands of charging stations, weather forecast data affecting solar generation and grid demand, historical usage patterns and user behavior models, and grid status information from utility providers. This multidimensional approach enables a comprehensive view of system state that would be impossible to maintain through human monitoring alone.

The system continuously analyzes this integrated data stream to generate contextually rich alerts such as:

...
ALERT [Medium Priority] - Station Cluster #143

Predicted overload condition in 45 minutes

Confidence: 82%

Context: Temperature increase, historical high usage pattern, limited grid capacity

Recommendation: Dynamic price adjustment to distribute the load

...

Recent research published in Energy and AI demonstrates the substantial operational benefits of predictive analytics in EV charging infrastructure management. This comprehensive study of large-scale charging networks found that AI-powered load prediction models can forecast demand patterns with accuracy exceeding 85% up to two hours in advance, providing critical lead time for implementing load management strategies. The analysis of multiple network deployments shows that operators implementing these predictive capabilities reduced grid constraint violations by an average of 62% while simultaneously improving charging session completion rates. Particularly notable was the finding that proactive load balancing through dynamic pricing signals and charging rate modulation consistently outperformed reactive approaches, both in terms of infrastructure utilization and customer satisfaction metrics [10].

In this operational model, the human operator functions as a strategic overseer rather than a reactive troubleshooter. When presented with an alert, they can review the prediction and supporting evidence, override the recommendation if necessary based on additional context, implement load-balancing measures proactively, and provide feedback on the alert's accuracy to improve future predictions. This collaborative intelligence approach combines the AI system's continuous analytical capabilities with human judgment regarding factors that may not be fully captured in the data model.

Challenges in EV Charging Infrastructure Management

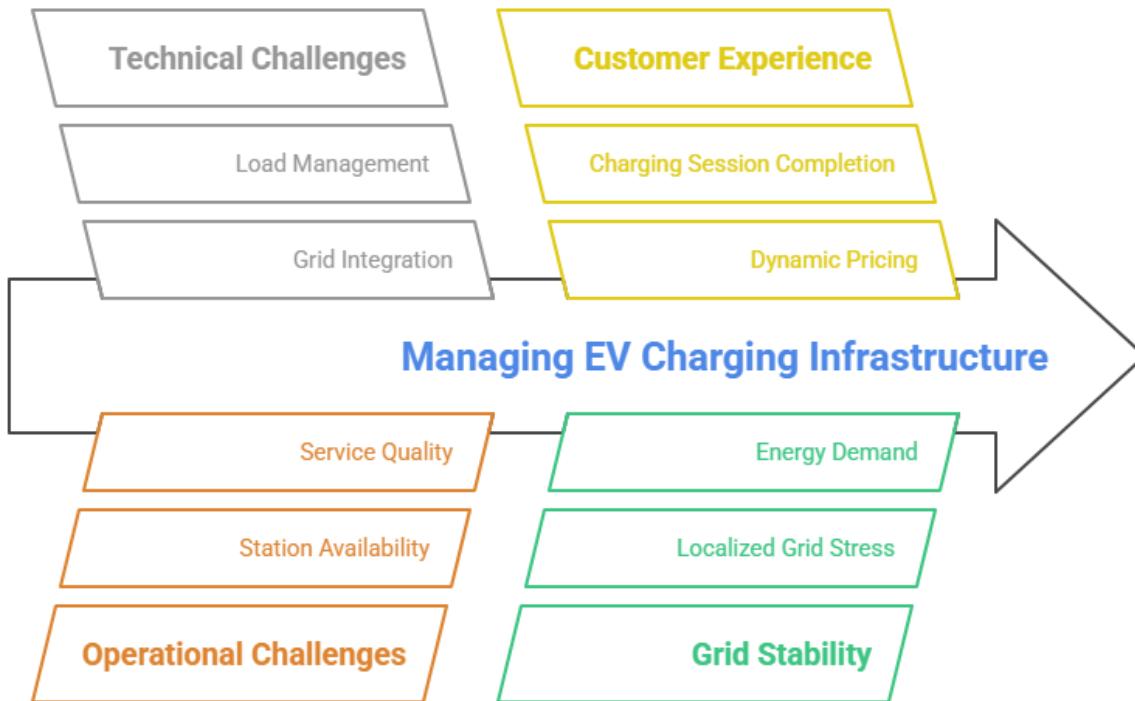


Fig 4: Challenges in EV Charging Infrastructure Management [9, 10]

6. The Changing Human Role

As alerting systems become more intelligent, the human role evolves from reactive troubleshooter to strategic overseer. This fundamental shift in operational paradigm creates several important dynamics that reshape how technical teams function and how organizations approach complex system management.

6.1 Complementary Expertise

AI excels at continuous monitoring and pattern recognition across vast datasets, while humans bring contextual understanding, domain expertise, and judgment to the equation. Analysis published in the Machine Learning Times emphasizes that the most successful intelligent systems implement thoughtful divisions of labor between human and artificial intelligence components. Their review of operational AI deployments found that organizations achieving the highest performance improvements consistently maintained human involvement in decision processes rather than pursuing full automation. These high-performing implementations explicitly design workflows around complementary capabilities—leveraging AI for continuous vigilance, pattern recognition, and historical analysis while preserving human authority for contextual interpretation and final decision-making. This balanced approach resulted in consistently better outcomes than either fully automated systems or traditional human-only monitoring approaches [11].

The most effective implementations are explicitly designed for this complementarity rather than treating human involvement as a transitional phase. These systems preserve clear domains of responsibility, with automated components handling continuous data analysis while reserving judgment calls and contextual interpretation for human specialists. This division leverages the unique strengths of each participant while minimizing their respective limitations.

6.2 Trust Calibration

Human operators must develop appropriate trust in AI-generated alerts, neither dismissing valid warnings nor accepting false positives without scrutiny. Research from the Defense Technical Information Center on human-autonomy teaming highlights the

critical importance of calibrated trust in operational settings. Their comprehensive analysis of trust dynamics across multiple domains identified consistent patterns where improper trust calibration significantly degraded system performance. Under-trust scenarios resulted in operators ignoring valid system recommendations and defaulting to less efficient manual processes, while over-trust created vulnerability to automation bias where operators accepted system outputs without appropriate critical evaluation [12].

Successful implementations address this challenge through transparency in how alerts are generated and providing performance metrics on system accuracy. By exposing confidence levels, supporting evidence, and historical performance statistics, these systems enable operators to develop appropriately calibrated trust—maintaining healthy skepticism while recognizing the system's proven capabilities. Some organizations implement formal calibration processes, periodically introducing known test cases to measure operator response patterns and identify any developing biases in either direction.

6.3 Knowledge Feedback Loop

Each human decision on an AI-generated alert creates valuable training data. When an operator dismisses an alert as a false positive or confirms a subtle prediction, this feedback improves the system's future performance. The most sophisticated implementations implement closed-loop learning systems where human decisions directly influence model behavior in subsequent analyses. This continuous improvement process enables the system to adapt to changing conditions and incorporate operational knowledge that might be difficult to capture through explicit programming.

6.4 Cognitive Load Management

Intelligent alerting systems must carefully manage the volume and prioritization of alerts to prevent operator fatigue and ensure critical issues receive appropriate attention. This involves sophisticated alert routing, aggregation, and prioritization techniques that match information delivery to human cognitive capacity.

7. Future Directions

The evolution of intelligent alerting systems continues along several promising paths that will further transform the relationship between human operators and automated monitoring capabilities. These emerging developments extend beyond incremental improvements to represent fundamental shifts in how organizations approach complex system oversight.

7.1 Multimodal Alerts

Future systems will likely incorporate diverse data sources beyond traditional telemetry, creating rich multimodal monitoring capabilities that more closely approximate human sensory perception. According to Emeritus's comprehensive analysis of multimodal AI applications, next-generation monitoring systems are increasingly integrating diverse data types to create more holistic operational awareness. Their research indicates that organizations implementing multimodal approaches—combining visual, audio, telemetry, and text analysis—consistently identify potential issues earlier and with greater accuracy than traditional single-mode monitoring systems. This integration creates monitoring capabilities that better mirror human inspection processes, where experienced operators naturally combine visual observation, sound recognition, and performance metrics to evaluate system health [13].

This integration of multiple data modalities enables more robust anomaly detection by identifying issues that might be subtle or invisible in any single data stream. For example, combined analysis of vibration telemetry with acoustic monitoring can distinguish between normal operational sounds and the specific audio signatures of impending mechanical failures. Similarly, visual inspection systems can detect physical changes like fluid leaks, component discoloration, or unusual wear patterns that would not register in performance telemetry until failure is imminent.

The implementation of these capabilities leverages recent advances in deep learning architectures optimized for multimodal data fusion. These models can identify complex correlations across different data types, creating a more comprehensive understanding of system state than would be possible through separate analysis of individual data streams. This approach more closely approximates the multisensory assessment that experienced human operators develop through years of field experience.

7.2 Autonomous Intervention

For some classes of alerts, systems may progress beyond notification to autonomous intervention—automatically implementing corrective actions for well-understood issues while keeping humans informed. Research from Palo Alto Networks on industrial control system security highlights both the opportunities and challenges associated with autonomous response capabilities in operational technology environments. Their analysis emphasizes that while automated interventions can significantly reduce response times for well-defined scenarios, implementing these capabilities requires careful consideration of safety parameters, failure modes, and system interdependencies. Organizations pioneering these approaches typically implement rigorous

validation processes and clearly defined operational boundaries to ensure that autonomous actions enhance rather than compromise overall system reliability [14].

These autonomous response capabilities typically follow a graduated implementation strategy, beginning with simple, low-risk interventions like restarting services or adjusting resource allocations within predefined safe boundaries. As confidence in the system's decision-making capabilities increases, the scope of autonomous interventions may expand to include more complex responses. However, even the most advanced implementations maintain clear boundaries around autonomous action, reserving complex or consequential interventions for human review.

The most successful implementations of autonomous intervention capabilities maintain transparent oversight, with human operators receiving clear notification of both the detected issue and the action taken. These systems preserve human authority to override or modify automatic responses while leveraging automation to reduce response latency for well-understood scenarios. This approach creates a scalable operational model where routine issues receive immediate attention while preserving human judgment for novel or complex situations.

7.3 Collaborative Intelligence Networks

Different alerting systems may begin sharing insights across organizational boundaries, creating collective intelligence networks that improve prediction accuracy for all participants. This emerging paradigm represents a significant evolution beyond traditional organization-specific monitoring, enabling broader pattern recognition and knowledge sharing across similar systems.

8. Conclusion

The transformation from reactive to proactive operations represents one of the most significant impacts of AI on operational workflows. By enabling earlier intervention, intelligent alerting systems reduce downtime, extend equipment lifespans, and allow human experts to focus on strategic improvements rather than emergency responses. As these systems continue to evolve, the most successful implementations will maintain humans as essential partners in the process, leveraging AI for continuous monitoring and initial analysis while relying on human judgment for final decisions and contextual understanding. This human-AI collaboration model represents not the replacement of human expertise, but its augmentation and elevation to more strategic roles. In domains like fleet management and EV infrastructure, this shift is already delivering measurable operational improvements. As the technology matures and expands to new domains, it can be expected that further refinement of the human-AI collaboration model will occur, with each component focusing on its unique strengths within an increasingly sophisticated alerting ecosystem.

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