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Physical-Digital ITSM Integration: *AI Video Analytics as the Emergent Intelligence Layer*

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Abstract: IT Service Management (ITSM) has historically been a digitally bounded discipline, limited to data artefacts such as logs, tickets, and network telemetry. This paper introduces Physical-Digital ITSM Integration (PDII) as a new paradigm wherein AI-powered video analytics, deployed on edge computing infrastructure, becomes the primary intelligence layer connecting the physical operational environment to ITSM workflows. Drawing on empirical research, industry case studies, and emerging AI capabilities including Vision Large Language Models (VLLMs), Small Language Models (SLMs) on edge hardware, and agentic orchestration architectures, this paper demonstrates that PDII represents a category-defining evolution of ITSM. The paper contextualises this evolution within India's industrial and regulatory landscape, including DPDP Rules 2025 and Industry 4.0 manufacturing imperatives, and concludes with a practical implementation framework and directions for future research.

Keywords: AI Video Analytics, ITSM, Edge AI, Physical-Digital Integration, Predictive Service Management, EdgeBox, Indoai, SLM, AIOps, DPDP 2025

I. INTRODUCTION

IT Service Management has long functioned as a digitally bounded discipline. Information Technology Service Management (ITSM) is a subset of Service. Science that focuses on IT operationssuch as service delivery and support[2]. Its inputs are service tickets, system logs, performance metrics, and network telemetry. Automating ticket classification and prioritization in IT Service Management (ITSM) systems has been the subject of growing research attention[1] Its outputs are incident resolutions, change approvals, and SLA reports. The physical world in which IT infrastructure operates e.g the factory floor, the data centre, the hospital ward, the logistics warehouse, etc has remained outside the ITSM data perimeter [3].

Until recently, capturing meaningful, structured intelligence from physical environments at the speed and scale required by ITSM workflows was computationally infeasible at an economical cost. That constraint has now dissolved. The introduction of AI into IT service management (ITSM), and more specifically security management, will address the means by which to lessen the impact of threats and need to give AI the ability to intelligently and automatically recover from possible risk, not just detect it[4].

AI-powered video analytics, deployed on edge computing hardware, can process high-resolution video feeds in real time, classify physical events with over 90% accuracy, generate structured alert payloads, and deliver actionable intelligence to ITSM platforms within seconds of event occurrence[5][6][7][8]. This capability makes possible what this paper terms Physical-Digital ITSM Integration (PDII) — the systematic fusion of physical environment intelligence into ITSM data architectures.

The significance of this integration is not cosmetic but practical and imperative. Research across financial services, healthcare and telecommunications sectors has documented that organisations integrating AI analytics into ITSM reduced Mean Time to Resolution (MTTR) by 30 to 60 percent, improved SLA compliance from below 85 percent to over 95 percent, and reduced unplanned downtime by up to 35 percent [9][10][11]. These results were achieved with analytics applied exclusively to digital data streams. The hypothesis formed in this paper is that incorporating the physical intelligence layer i.e real-time AI video analytics, will produce improvements of comparable or greater magnitude[12], because the physical world contains precursor signals that digital systems detect only after physical causation has already occurred [13].

II. LIMITATIONS OF CURRENT ITSM ANALYTICS ARCHITECTURES

AIOps represents a significant advancement in IT operations, driven by the integration of AI and ML technologies[X—IX 14] though present ITSM analytics architectures, even those enhanced by Big Data platforms and AIOps tools, share

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a fundamental structural limitation: they are reactive to physical causation through five key capabilities: intelligent alert correlation that reduces noise by up to 87%, anomaly detection that identifies issues before traditional thresholds are breached, automated root cause analysis that eliminates manual correlation efforts, contextual enrichment of incidents, and automated remediation workflows that can resolve up to 62% of common issues without human intervention[15]. Network anomalies, server performance degradation and application failures are digital symptoms of events that originate in the physical world like hardware stress, thermal conditions, power fluctuations, human operational errors and equipment deterioration [16][17][18].

Enterprise Management Associates (EMA) research across 400 global ITSM practitioners identified that the most common primary use cases for AI and analytics in ITSM were shared AIOps at 30 percent, incident response analytics at 19 percent, and governance analytics at 18 percent [19]. Notably absent from this taxonomy is any category representing physical environment intelligence, reflecting the current blind spot in ITSM data architecture.
In ITIL, an incident is defined as an event that causes a service outage or degradation. For example, a server crash preventing users from accessing an application, a network failure slowing down internal systems, or a software bug causing repeated errors all qualify as incidents[20].

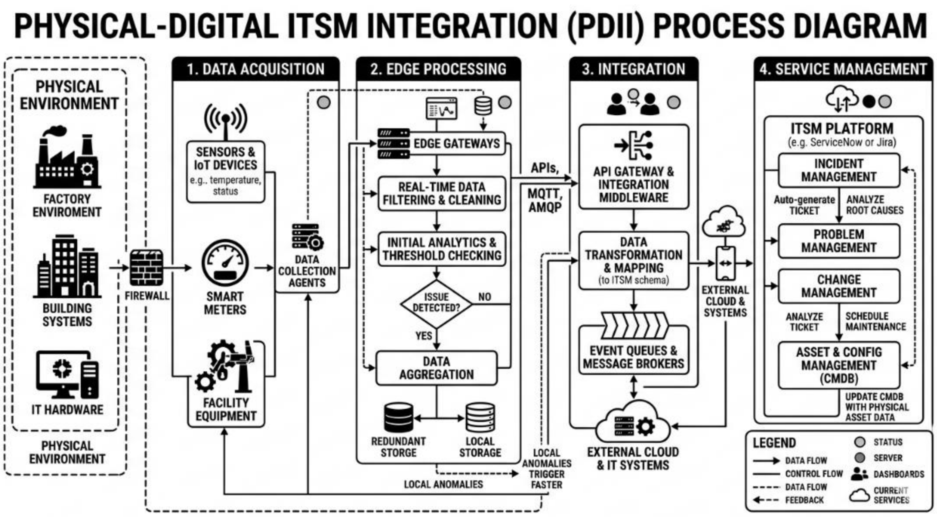
Incident Management refers to a structured process involving strategies, measures, policies, procedures, equipment, and trained staff to detect, mitigate, and resolve cybersecurity incidents in organizations[21]. Incident management is a structured process to restore services to normal as quickly as possible following a disruption[22]

Thus, ITSM frameworks such as ITIL 4 and COBIT define incident detection as the receipt of an alert or user report, both of which are generated after a physical condition has already manifested as a service impact [23]. By the time a ticket is raised, the physical causal chain is complete. Research by Ramaswamy and Sankaran (2024) characterised this as the central failure mode of reactive ITSM, noting that IT departments typically responded to incidents after they occurred, focusing on minimising downtime rather than preventing issues before they arose [11].

The gap this paper addresses is architectural, not analytical. Adding more sophisticated algorithms(AIOp, etc) to digitally bounded data pipelines cannot solve the fundamental problem that the physical precursors of most IT service incidents are invisible to those pipelines.

III. THE PHYSICAL-DIGITAL ITSM INTEGRATION (PDII) FRAMEWORK

The author defines Physical-Digital ITSM Integration (PDII) as a systematic architectural approach(see below PDII process diagram) in which AI-powered video analytics, operating on edge computing infrastructure, continuously processes physical environment data and delivers structured intelligence payloads to ITSM platforms, enabling predictive, automated and evidence-based service management.



The provided diagram illustrates a comprehensive architectural approach known as Physical-Digital ITSM Integration (PDII), designed to transform physical environmental data into AI-driven IT Service Management actions. The workflow progresses logically through five distinct, interconnected stages.

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The process begins with "Physical Environment Data Acquisition," where diverse inputs from video cameras, environmental and humidity sensors, IoT devices, and motion detectors generate a "Continuous Data Stream." This stream is channeled to the "Edge Computing Infrastructure," which processes and analyzes data locally using edge gateways and a powerful AI Video Analytics engine. This engine handles object detection, behavior identification, and event correlation, keeping sensitive processing close to the data source.

From the Edge, the processed data flows to the "Integration Layer," where it is transformed into a "Structured Intelligence Payload." This layer manages critical ETL (Extract, Transform, Load) tasks like data filtering and schema mapping, ensuring secure API-based delivery to the "ITSM Platform." The ITSM platform, which includes components like the modern Service Desk, Asset Management, and the CMDB (Configuration Management Database), ingests these intelligence payloads to drive incident and service actions.

The final stage details the "PDII Enabled Outcomes," which demonstrate the tangible business value of this integration: Predictive Service Management, Automated Service Actions, Evidence-Based Decisions, and Optimized Physical Infrastructure.

PDII is distinguished from prior attempts to integrate physical monitoring into ITSM such as IoT sensor integration and building management system connectivity by three characteristics: contextual richness, predictive depth and autonomy of response generation.

3.1 Contextual Richness

Unlike point sensors that report a single scalar value such as a temperature reading, AI video analytics reports contextual events with full situational detail. For example: an operator at a workstation is not wearing required safety equipment, and this is the second occurrence within thirty minutes. This contextual richness enables ITSM systems to generate meaningful incident classifications rather than raw threshold alerts, dramatically reducing false positive rates and cognitive load on operations teams[24-25]. Empirical studies demonstrate that ITSM automation can reduce deployment lead times by up to 70%, decrease rollback incidents by 40%, and enhance audit readiness in regulated sectors[26].

3.2 Predictive Depth

Machine learning algorithms **can** build a **model** based on **training data** of a particular problem domain, **to** make predictions or decisions[27]. AI video models trained on historical visual data can detect precursor patterns — equipment vibration anomalies, material accumulation in conveyors, human fatigue indicators — that precede measurable service impact by minutes or hours. This precursor-detection capability converts ITSM from a reactive to a genuinely predictive discipline [13].

3.3 Autonomy of Response

Agentic AI for ITSM combines reasoning (LLMs) with orchestrated execution to autonomously resolve incidents across systems - reducing L1/L2 ticket volume by up to 60–80% while improving MTTR and service quality[28].
Edge AI architectures, augmented by agentic orchestration layers, can understand context[29] and autonomously generate structured ITSM payloads — incident tickets with classification, priority, and evidence attachments — without human intervention in the detection-to-ticket pipeline. EMA research found that 84 percent of ITSM leaders rated combining AI analytics with automation as a high or extremely high priority [19]. PDII provides the physical intelligence necessary to make that combination operationally complete.

IV. PDII TRANSFORMATION OF CORE ITSM PROCESSES

The four core ITSM processes defined by ITIL 4 are each fundamentally transformed under the PDII framework. The following subsections examine each process in turn [23].

4.1 Incident Management

Incident Management restores normal **service** operation while minimizing **impact** to business operations and maintaining quality[30]. Traditional incident management is triggered by digital failure reports generated after a service impact has already occurred. Under PDII, incident management is triggered by physical precursor detection before impact occurs. A camera detects smoke accumulation, an operator bypassing a safety protocol, or machine vibration outside its normal envelope, and an ITSM incident ticket is auto-generated within seconds. Documented implementations have reduced MTTR by 30 to 60 percent [11].

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4.2 Change Management

Change Management is the process of planning, approving, and implementing **changes** to IT systems and services in a way that minimizes disruptions[31]. Change management traditionally monitors digital dashboards for post-change impact. PDII adds visual verification of physical change outcomes in real time. Lee, Bagheri, and Kao (2015) propose a 5C architecture (Connection, Conversion, Cyber, Cognition, Configuration) for implementing Cyber-Physical Systems (CPS) in Industry4.0 . This framework transforms raw machine data into actionable intelligence, enabling predictive maintenance, self-awareness, and optimized performance in manufacturing systems. When a firmware update is applied to robotic controllers, video analytics confirms that the physical behaviour of the system matches the intended outcome, closing the verification loop that digital monitoring alone cannot provide [32].

4.3 Problem Management

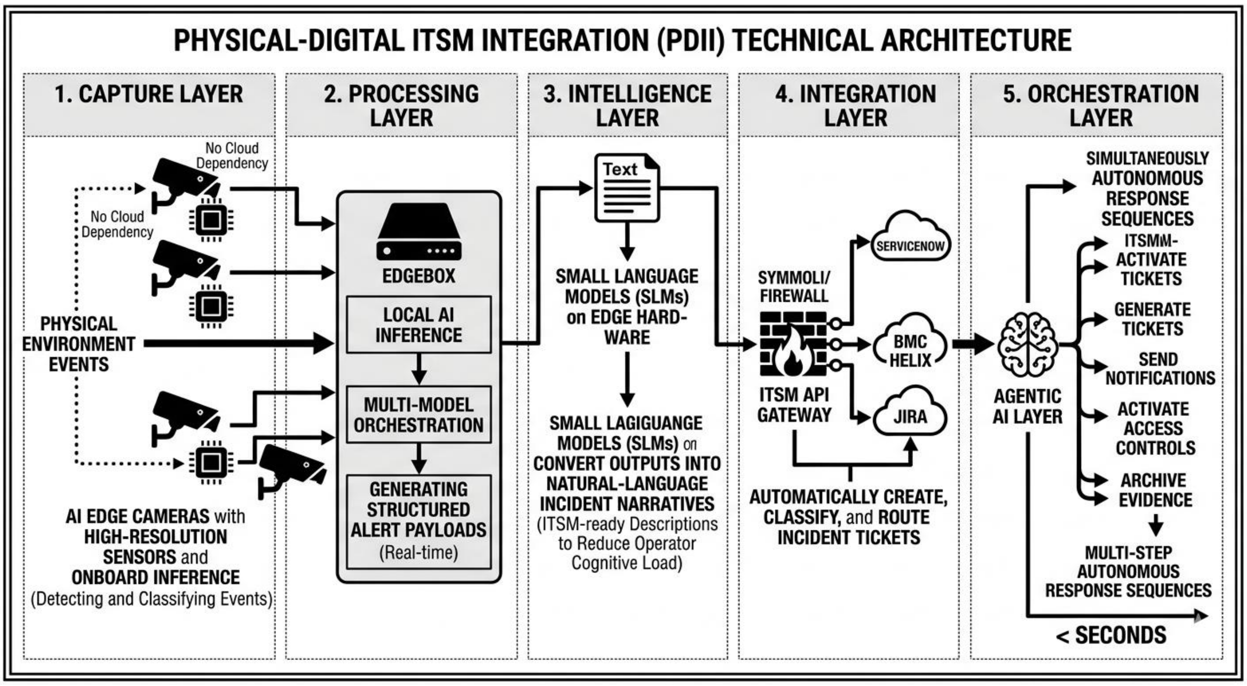
Problem management is the process of **identifying, managing and finding solutions for the root causes of incidents** on an IT service[33] . Problem management, which aims to identify root causes of recurring incidents[34], gains a new analytical dimension through PDII. Visual pattern correlation across physical and digital event streams allows AI models to surface correlations between physical conditions and recurring digital incidents, converting hypothesis-driven forensic investigation into evidence-based pattern recognition [11].

4.4 Service Level Management

Traditional SLA management relies heavily on **predefined metrics and thresholds**, with manual interventions often required to resolve issues[35]. SLA management traditionally relies on digital proxies and self-reported metrics. PDII provides objective, timestamped physical evidence integrated into the SLA audit trail. Visual records of technician response times, maintenance activities, and production throughput rates become part of the SLA compliance record, eliminating disputes that arise from the absence of verifiable physical service delivery evidence [36].

V. ENABLING TECHNOLOGY STACK FOR PDII

The technical architecture(see below diagram) that enables PDII combines five integrated capability layers, operating in sequence from physical observation to automated ITSM response.



- Capture Layer: AI edge cameras with high-resolution sensors and onboard inference capability serve as the physical observation point, detecting and classifying events without cloud dependency.
- Processing Layer: The EdgeBox provides local AI inference and multi-model orchestration, processing feeds from multiple cameras and generating structured alert payloads in real time.

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- Intelligence Layer: Small Language Models (SLMs) running on edge hardware convert classification outputs into natural-language incident narratives, producing ITSM-ready descriptions that reduce operator cognitive load [37].
- Integration Layer: An ITSM API gateway connects EdgeBox alert outputs to ITSM platforms such as ServiceNow, BMC Helix, or JIRA, automatically creating, classifying, and routing incident tickets.
- Orchestration Layer: An agentic AI layer enables multi-step autonomous response sequences — simultaneously generating tickets, sending notifications, activating access controls, and archiving evidence — within seconds of physical event detection [38].

The edge-first architecture is not merely a cost optimisation. It is the prerequisite for real-time ITSM integration. Cloud round-trip latency makes sub-second detection-to-ticket generation impossible. Edge processing also maintains video data within the physical premises, satisfying data sovereignty requirements and reducing the regulatory surface area for compliance obligations [39].

5.1 Vision LLMs and SLMs at the Edge

A significant 2026 development for PDII is the emergence of Small Language Models capable of running inference on edge hardware without cloud dependency[40-41]. SLMs convert classification codes into actionable natural-language event descriptions at the point of detection [42]. This capability is qualitatively different from prior video analytics outputs and materially improves ITSM triage speed and accuracy.

5.2 Agentic Orchestration

Agentic AI frameworks are being deployed across sectors where autonomy and adaptability are essentia [43]. Agentic AI architectures allow a single physical detection event to trigger a coordinated, multi-step organisational response without human initiation at any step. This realises the ITSM automation vision that 84 percent of EMA survey respondents identified as their highest priority outcome from AI and analytics investments [19].

VI. PDII IN THE INDIAN INDUSTRIAL AND REGULATORY CONTEXT

India's industrial landscape presents a unique convergence of opportunity and urgency for PDII adoption. Government Production Linked Incentive (PLI) schemes across twelve manufacturing sectors are catalysing rapid capacity expansion among mid-sized enterprises that are building IT and operational infrastructure largely from scratch, without legacy ITSM architectures to retrofit [44].This greenfield opportunity allows Indian manufacturers to implement PDII-native architectures, where AI video analytics and ITSM integration are designed as unified systems from inception rather than as afterthoughts to existing tooling. The India-specific leapfrog potential is analogous to the country's mobile payments adoption, which bypassed the card infrastructure stage entirely.

India's Digital Personal Data Protection (DPDP) Rules 2025 impose requirements on any AI system that processes visual data involving individuals: purpose disclosure, data minimisation, defined retention periods, and prohibition of use beyond the stated purpose [15]. PDII architectures designed with edge processing, where video never leaves the premises and only structured non-personal alert data is transmitted, are intrinsically better positioned for DPDP compliance than cloud-dependent video analytics deployments.

VII. IMPLEMENTATION READINESS FRAMEWORK

Based on the technology analysis and case study evidence synthesised in this paper, the following five-stage implementation framework diagram is proposed for organisations pursuing PDII adoption.

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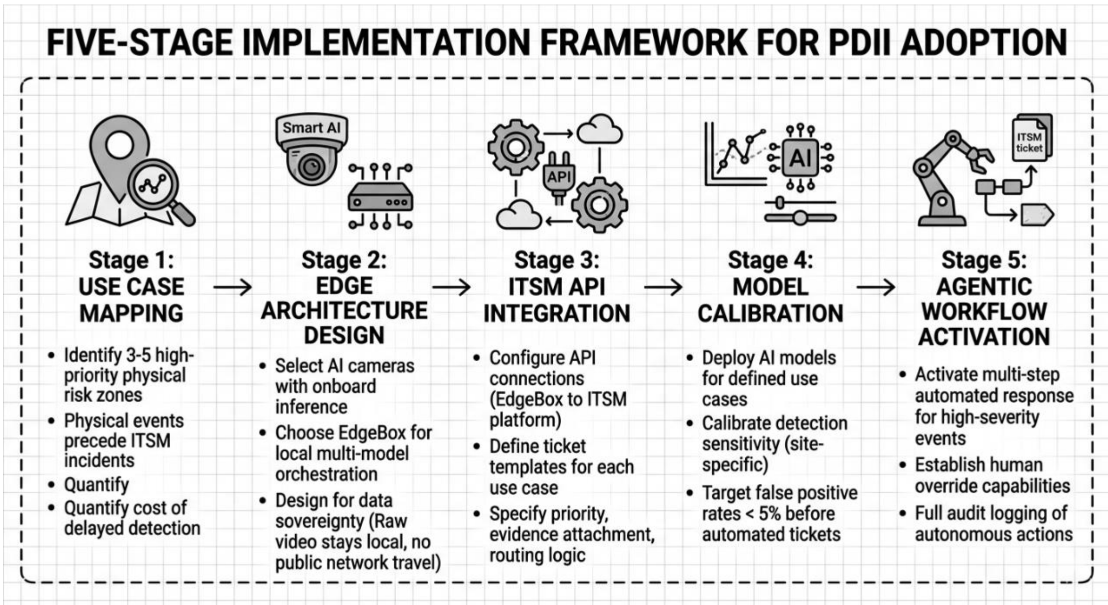

- Stage 1 - Use Case Mapping: Identify three to five high-priority physical risk zones where physical events demonstrably precede ITSM incidents. Quantify the current cost of delayed detection in each zone.
- Stage 2 - Edge Architecture Design: Select AI camera hardware with onboard inference capability and an EdgeBox for local multi-model orchestration. Design for data sovereignty compliance from the outset, ensuring raw video does not traverse public networks.
- Stage 3 - ITSM API Integration: Configure API connections between the EdgeBox alert output and the target ITSM platform. Define ticket templates for each use case, including priority classification, evidence attachment protocol, and routing logic.
- Stage 4 - Model Calibration: Deploy AI models for defined use cases and calibrate detection sensitivity against site-specific conditions. Target false positive rates below five percent before enabling automated ticket generation.
- Stage 5 - Agentic Workflow Activation: Once accuracy targets are met, activate multi-step automated response workflows for high-severity event categories. Establish human override capabilities and full audit logging for all autonomous actions.

Success factors identified in EMA research are directly applicable to PDII implementations: CIO-level executive sponsorship, clearly defined success metrics established before deployment, integration with existing ITIL process governance, and sustained investment in team capability development [19].

VIII. CONCLUSION

This paper has introduced Physical-Digital ITSM Integration (PDII) as a new conceptual and architectural framework for IT Service Management. The core argument is straightforward and empirically established: physical events cause digital service impacts. ITSM systems that cannot observe the physical world are structurally limited to reactive, post-causation response.

AI video analytics, deployed on edge hardware with Vision LLM and SLM capabilities and connected to ITSM platforms through agentic orchestration layers, eliminates this structural limitation. The documented evidence from analytics-enhanced ITSM — 30 to 60 percent MTTR reduction, SLA compliance improvements from below 85 percent to over 95 percent — was achieved without physical intelligence integration. PDII represents the next advancement: bringing the full causal chain of service events within the observable and actionable scope of the ITSM platform.

For Indian enterprises, the convergence of greenfield manufacturing expansion, DPDP regulatory structure[15], and the commercial availability of indigenous AI camera and EdgeBox technology creates a rare opportunity to build PDII-native operational infrastructure from the ground up. Organisations that capitalise on this window will operate with a qualitatively different category of situational awareness — one in which the camera, the edge AI model, and the ITSM platform form a unified, continuously learning, autonomously responding operational system.

Future research directions include: longitudinal measurement of MTTR and SLA improvements attributable specifically to physical intelligence integration; comparative analysis of PDII effectiveness across manufacturing, logistics, healthcare, and financial services sectors; development of standardised PDII maturity models analogous to ITIL capability maturity frameworks; and privacy-preserving design patterns that satisfy DPDP 2025 requirements while maximising operational intelligence value.

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