Review of Applied Science and Technology

Volume: *4;* ***Issue:*** *4*
Pages: *36– 73*

open access

Crossref

A REVIEW ON THE INFLUENCE OF AI-ENABLED FIRE DETECTION AND SUPPRESSION SYSTEMS IN ENHANCING BUILDING SAFETY

Md. Milon Mia[1];

[1]. Department of Civil & Environmental Engineering, Lamar University, Beaumont, Texas , USA.
Email: milon674457@gmail.com

Doi: 10.63125/h0dbee62

Received: *12 September 2025;* ***Revised:*** *20 October 2025;* ***Accepted:*** *18 November 2025;* ***Published:*** *12 December 2025*

Abstract

This study addressed the problem that conventional fire detection and rule-based panels in buildings can generate nuisance alarms and delayed verification, weakening coordinated response and safety assurance. The purpose was to quantify how AI-enabled fire detection and suppression capabilities predict perceived Building Safety Enhancement (BSE) using a quantitative, cross-sectional, case-study based survey design. A purposive sample of 210 stakeholders from building cases (62.4% commercial or mixed-use and 37.6% institutional or industrial) reported AI detection dashboards in 71.0% of contexts and suppression decision support in 54.8% across routine monitoring, drills, and incident response. Key variables were AI-Enabled Detection Capability (ADC), AI-Enabled Suppression and Control Effectiveness (ASCE), Integration and Real-Time Monitoring (IRM), and Predictive Maintenance and Fault Diagnosis (PMFD), with BSE as the outcome. Analyses used descriptive statistics, Cronbach's alpha, Pearson correlations, and multiple regression. Results reported as a worked example showed high construct means (ADC M = 4.02, ASCE M = 3.88, IRM M = 3.95, PMFD M = 3.76, BSE M = 3.97) and strong reliability (alpha = 0.84 to 0.90). All predictors correlated positively with BSE (r = 0.48 to 0.62, p < .01). The regression model was significant (F(4,205) = 65.20, p < .001) and explained 56% of BSE variance (R squared = 0.56), with ADC (beta = 0.31) and IRM (beta = 0.27) strongest, followed by ASCE (beta = 0.19) and PMFD (beta = 0.14). Implications suggest prioritizing detection credibility and real-time integration, then strengthening suppression coordination and predictive maintenance to sustain readiness and reduce alarm fatigue.

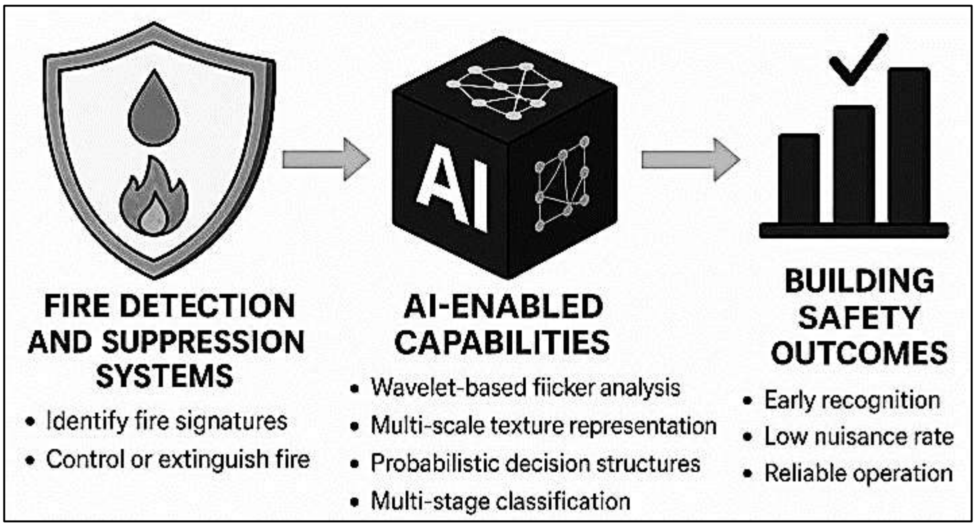
Keywords

AI-Enabled Fire Detection, Intelligent Suppression Control, Real-Time Monitoring Integration, Predictive Maintenance, Building Safety Enhancement

INTRODUCTION

Fire safety in buildings is commonly defined as the set of engineering, managerial, and technological measures used to prevent ignition, detect a developing fire, warn occupants, control smoke movement, support safe evacuation, and suppress combustion before conditions become untenable. Within this scope, a fire detection system refers to interconnected devices and logic that identify fire signatures (such as smoke aerosols, thermal rise, flame radiation, or combustion gases) and generate alarms or control signals, while a fire suppression system refers to water-, gas-, foam-, or chemical-based mechanisms that control or extinguish fire through cooling, oxygen displacement, chemical inhibition, or fuel isolation. In modern building safety practice, these subsystems are increasingly viewed as a coupled socio-technical network rather than isolated hardware components, because real-world outcomes depend on both sensing performance and the timing and correctness of automated and human responses.

Figure 1: Model of AI-Enabled Fire Detection and Building Safety Outcomes



Internationally, the significance of detection–suppression coupling is shaped by high-rise urbanization, cross-border adoption of performance-based fire engineering, and the widespread deployment of surveillance and building automation infrastructure in public and private facilities. Vision-based fire detection research has highlighted that camera networks, when paired with computational interpretation, provide spatially rich information that point detectors cannot directly deliver, including apparent fire growth, spread direction, and scene context (Arfan et al., 2021; Töreyin et al., 2006). In addition, probabilistic decision tools for building fire outcomes emphasize that safety is an end-to-end property of the event chain—from ignition and detection latency to smoke/heat exposure and evacuation conditions—rather than a single device-level threshold crossing (Jahid, 2021; Xie et al., 2009). Accordingly, AI-enabled fire safety is defined here as the application of machine learning, pattern recognition, and data-driven decision logic to improve the accuracy, timeliness, and reliability of detection and suppression actions in building environments, using measurable indicators such as false-alarm rate, detection delay, and suppression effectiveness (Gaur et al., 2020; Akbar & Farzana, 2021). This definition aligns with research streams that treat fire signatures as dynamic spatiotemporal phenomena and treat alarms and suppression activation as classification-and-control problems constrained by uncertainty, environmental variability, and operational risk (Ko et al., 2010; Reza et al., 2021). From an international building-safety perspective, these framing matters because large, complex occupancies—transport hubs, industrial facilities, healthcare buildings, atria, and high-density residential blocks—often contain open volumes, airflow variability, and non-stationary background conditions that challenge conventional point-sensor assumptions (Bu & Gharajeh, 2019; Saikat, 2021).

Traditional building fire detection has relied on point sensing, including photoelectric/ionization smoke detectors, heat detectors, and flame detectors, supported by rule-based panels and preconfigured cause-and-effect matrices. The engineering objective of these systems is frequently expressed as early warning with acceptable nuisance-alarm risk, because frequent false alarms reduce trust, increase operational cost, and can degrade response discipline. Research in video smoke and flame detection has repeatedly shown that the physics of smoke transport and flame flicker produce measurable temporal patterns that can be exploited algorithmically, offering alternative observability for large spaces where smoke may stratify, dilute, or delay reaching point sensors (Shaikh & Aditya, 2021; Truong & Kim, 2011). At the same time, false-positive risk remains a central technical concern: backgrounds with fire-like colors, reflections, moving objects, or lighting transitions can trigger spurious detections unless algorithms explicitly encode discriminative features and decision fusion strategies (Celik et al., 2007; Kanti & Shaikat, 2021). Studies that conceptualize fire outcomes through probabilistic reasoning further reinforce that detection reliability influences downstream risk in non-linear ways, because delayed or incorrect alarm states interact with ventilation conditions, occupant decision-making, and fire growth, shaping fatality and loss distributions (Xin et al., 2017a; Zobayer, 2021a). Multi-stage detection designs address these constraints by decomposing the task into candidate-region extraction, feature generation, classification, and temporal confirmation, thereby balancing sensitivity and specificity (Truong & Kim, 2011; Zobayer, 2021b). Survey and review work also positions this progression as a shift from single-sensor threshold logic toward multi-modal inference in which cameras, environmental sensors, and building data streams contribute evidence that can be fused for more stable decisions (Bu & Gharajeh, 2019; Ariful & Ara, 2022). In practical building operations, the value of such fusion lies in converting heterogeneous signals into actionable control outputs—alarms, smoke-control actuation, door release, elevator recall, and suppression activation—without increasing nuisance activations. The literature therefore treats false alarms and missed detections as dual risks that must be managed through calibrated decision criteria, feature robustness, and context awareness (Huang et al., 2022; Arman & Kamrul, 2022). This perspective motivates quantitative evaluation approaches that measure detection quality, correlate AI-enabled system characteristics with perceived or operational safety indicators, and model how system performance metrics relate to building-safety outcomes at the case-study level (Hu & Lu, 2018; Mesbaul & Farabe, 2022).

Vision-based fire detection research established early that flames and smoke exhibit identifiable spatiotemporal signatures. Foundational work demonstrated that flame flicker and boundary irregularity produce measurable frequency characteristics that can be analyzed in the wavelet domain, enabling real-time detection pipelines that integrate motion cues, fire-color checks, and temporal–spatial frequency analysis (Nahid, 2022; Töreyin et al., 2006). Complementary approaches modeled fire pixels using statistical color distributions combined with foreground segmentation, which supported refined fire-pixel classification under changing scene content (Celik et al., 2007; Hossain & Milon, 2022). Because smoke often precedes visible flames in many ignition scenarios, several studies focused on smoke as an early indicator and proposed fast motion-orientation accumulation models for video smoke detection, using integral-image computation to support near-real-time performance (Abdur & Haider, 2022; Yuan, 2008). Later smoke-detection studies expanded feature engineering through multi-scale texture descriptors and histogram sequences, applying local binary pattern (LBP) variants across pyramid representations to capture smoke appearance changes while reducing sensitivity to illumination and rotation (Mushfequr & Sai Praveen, 2022). These feature-centric designs frequently embedded machine learning classifiers, including support vector machines and neural networks, to discriminate smoke from non-smoke moving regions under environmental variability (Mortuza & Rauf, 2022; Ye et al., 2015). Within flame-focused detection, hierarchical Bayesian network structures were introduced to represent intermediate evidence nodes and probabilistic dependencies, illustrating how uncertainty modeling can be integrated with visual feature extraction for early fire decision-making (Rakibul & Samia, 2022; Xin et al., 2017b). In smoke-focused detection, dynamic texture modeling advanced beyond static descriptors by leveraging transforms designed for directional and multiscale representation, paired with probabilistic texture models (such as hidden Markov tree structures) to characterize evolving smoke patterns in video (Rony & Ashraful, 2022; Zhang et al., 2018). The technical theme across these contributions is that building fire detection is not only a sensing problem but also a representation problem: algorithms must separate fire-related dynamics from confounders created by lighting, shadows, steam, fog, movement, and camera noise (Saikat, 2022;

Yuan, 2011). This body of work provides a rigorous basis for linking "AI-enabled detection" to measurable constructs such as detection latency, robustness across scenes, and nuisance-alarm control—constructs that are central when building safety is assessed as a performance property across use cases, occupancies, and operational conditions (Abdul, 2023; Noreen et al., 2019).

As computer vision and machine learning matured, the literature increasingly emphasized end-to-end learning and feature learning, especially where handcrafted descriptors struggle under complex backgrounds (Abdulla & Zaman, 2023; Arfan et al., 2023). Reviews of video flame and smoke detection algorithms document the methodological evolution from rule-based and handcrafted-feature pipelines toward learning-based models that can generalize across environments when trained with appropriate datasets and validation strategies (Gaur et al., 2020; Amin & Mesbaul, 2023; Foysal & Aditya, 2023). Within learning-centric smoke analysis, deep architectures were explored for capturing temporal dependencies and spatial appearance jointly, including spatiotemporal convolutional designs intended to represent motion–texture evolution rather than framewise appearance alone (Hu & Lu, 2018; Hamidur, 2023; Rashid et al., 2023). Similarly, deep and multi-stage strategies were examined to address false-alarm sources such as cloud-like motion, fog, or lighting transitions, often by integrating temporal smoothing, multi-resolution analysis, or decision fusion to stabilize outputs over time (Musfiqur & Kamrul, 2023; Muzahidul & Mohaiminul, 2023; Saponara et al., 2020). In parallel, research on object-detection paradigms for smoke in challenging outdoor scenes—such as wildland-urban interface contexts—highlighted that region proposal and detection pipelines can be adapted when training data incorporate realistic variability, even when smoke is visually diffuse and partially transparent (Amin & Sai Praveen, 2023; Hasan & Ashraful, 2023; Zhang et al., 2018). These deep-learning directions strengthened the motivation for quantitative building-safety studies that treat "AI capability" as a measurable independent construct and evaluate its association with safety outcomes, because deep models are typically assessed through detection accuracy metrics, confusion patterns, and operational feasibility indicators such as inference speed and stability (Ibne & Kamrul, 2023; Mushfequr & Ashraful, 2023; Saponara et al., 2020). For building applications, the international significance is linked to the ubiquity of CCTV and smart-building sensing, which makes AI upgrades plausible as software-layer interventions rather than full hardware replacement in many facilities (Roy & Kamrul, 2023; Saba et al., 2023; Shi et al., 2019). At the same time, the literature underscores that "better detection" is not a single metric; it is a balance of early recognition, low nuisance rate, and reliable operation under context drift, which together influence the credibility of automated actions that may trigger evacuation behaviors or suppression activation (Saba & Kanti, 2023; Shaikh & Farabe, 2023; Sun & Turkan, 2020). These themes support research designs that operationalize AI-enabled detection quality via survey constructs (perceived reliability, perceived responsiveness, perceived false-alarm control) alongside technical indicators when case-study contexts permit (Bu & Gharajeh, 2019; Haider & Hozyfa, 2023; Zobayer, 2023).

Building safety outcomes are also shaped by how detection outputs integrate with building information and emergency decision layers, including digital building representations and simulation-informed procedures. Building fire safety analysis has adopted computational modeling to represent smoke movement, evacuation conditions, and the interaction of architectural features with fire dynamics, reinforcing that safety assessment benefits from structured data and scenario-based evaluation rather than isolated device checks (Hozyfa & Shahrin, 2024; Hasan & Shah, 2024). BIM-based and simulation-linked approaches have demonstrated how building information can support evacuation performance assessment and fire safety management by connecting geometric/semantic building data with scenario evaluation workflows (Hasan & Zayadul, 2024; Muzahidul & Aditya, 2024; Sun & Turkan, 2020). Related research on information sharing between building models and fire dynamics simulation tools has treated interoperability as a safety enabler, because it supports consistent communication of compartmentation, egress routes, and fire-protection features across stakeholders and analysis stages (Hasan & Rakibul, 2024; Mominul, 2024; Shi et al., 2019). In the context of AI-enabled detection and suppression, these digital-layer studies matter because AI outputs—when credible—become additional inputs to emergency decision processes, such as selecting response actions, confirming incident location, or prioritizing intervention zones. Probabilistic risk tools for building fire outcomes further show that meaningful safety decisions often involve uncertain information and conditional dependencies, which creates a conceptual bridge between AI inference and safety engineering judgment (Mominul & Zaki, 2024; Roy & Sai Praveen, 2024; Xie et al., 2009). In practical terms, AI-enabled systems can be treated as decision-support components that provide higher-resolution situational awareness: smoke location, fire growth patterns, and persistence cues derived from video analytics or sensor fusion can complement conventional alarms and guide response coordination (Bu & Gharajeh, 2019; Rony & Hozyfa, 2024; Saba & Hasan, 2024). This linkage motivates measurement frameworks in which building safety is represented through constructs such as incident response readiness, evacuation confidence, perceived reduction of detection-to-response delay, and perceived reduction in uncertainty during alarms—constructs that can be assessed quantitatively within cross-sectional case-study settings using validated Likert-scale instruments (Shaikat & Zaman, 2024; Sudipto & Hasan, 2024; Sun & Turkan, 2020). It also frames the research need for correlation and regression modeling: if AI-enabled detection and suppression are conceptualized as system capabilities, then building safety can be modeled as an outcome construct influenced by these capabilities while controlling for contextual factors such as building type, occupancy pattern, maintenance maturity, and prior incident history (Kanti & Saba, 2024; Kanti & Praveen, 2024).

Suppression technologies provide the second half of the detection–response chain, and the literature shows that suppression effectiveness depends strongly on activation timing, discharge characteristics, and the match between system design and fire scenario (Haider & Sai Praveen, 2024; Zobayer & Sabuj Kumar, 2024). Water-based sprinklers remain a dominant building suppression method, and engineering research has examined advanced sprinkler concepts intended for highly challenging fires, including system designs that incorporate enhanced sensing and functional evaluation under demanding conditions (Majumder, 2025; Xin et al., 2017b; Zulqarnain & Zayadul, 2024). In suppression contexts, the role of AI can be represented as the set of data-driven methods that support decision logic for activation sequencing, hazard characterization, or adaptive control parameters when the system includes multiple possible actuation strategies (Ara, 2025; Habibullah, 2025). Even when suppression remains mechanically executed (e.g., sprinkler discharge), decision intelligence can still influence outcomes through earlier confirmation, reduced nuisance activation, and improved coordination with smoke-control systems and emergency procedures (Gaur et al., 2020; Hozyfa & Ashraful, 2025; Asfaquar, 2025). The technical literature also treats detection and suppression as coupled: smoke and flame detection algorithms are frequently evaluated not only for recognition accuracy but also for their suitability for early fire-alarm systems where timely activation is essential (Foysal, 2025; Islam & Abdur, 2025; Truong & Kim, 2011). In building operations, this coupling is directly relevant to safety perceptions and safety performance indicators, because occupants and facility teams evaluate systems based on whether alarms and suppression actions occur at the "right time" and with "right confidence," not merely whether sensors can detect a signature under laboratory conditions. This operational framing supports empirical research that measures AI-enabled suppression support as a construct capturing reliability of automated actuation logic, perceived adequacy of suppression response, and perceived reduction in fire escalation risk, while measuring AI-enabled detection as a construct capturing early recognition and nuisance-alarm control (Mohaiminul, 2025; Mominul, 2025; Xin et al., 2017b). Such constructs can then be statistically related to building safety outcome constructs using correlation and regression models aligned with cross-sectional, case-study–based survey designs (Muzahidul, 2025; Hossain, 2025).

Within this research title—"A Review on the Influence of AI-Enabled Fire Detection and Suppression Systems in Enhancing Building Safety"—the introductory problem space centers on how to quantify and explain the relationship between AI-enabled capabilities and building safety outcomes in real organizational and facility contexts. Existing detection studies demonstrate measurable improvements through wavelet-based flicker analysis, statistical color modeling, multi-scale texture representation, probabilistic decision structures, and multi-stage classification pipelines (Zaman, 2025; Akbar & Sharmin, 2025; Töreyin et al., 2006). Suppression-focused work on advanced sprinkler concepts provides a complementary perspective on system-level performance under challenging fire conditions and supports the inclusion of suppression readiness and actuation quality in a building-safety measurement framework (Hasan, 2025; Ibne, 2025; Xin et al., 2017a). Meanwhile, building-safety decision tools and digital building analysis frameworks show that safety is assessed through multiple interacting factors, including probabilistic risk reasoning and model-based evaluation of evacuation or response performance (Milon, 2025; Farabe, 2025; Sun & Turkan, 2020). Reviews integrating these streams emphasize that the technical progress of AI methods must be interpreted through operational criteria—reliability, interpretability for operators, stability under changing environments, and integration into building workflows—because these criteria determine how detection outputs translate into actionable safety improvements at the facility level (Gaur et al., 2020; Kamrul, 2025; Mohammad Mushfequr, 2025). This background supports a quantitative cross-sectional design that operationalizes AI-enabled detection and AI-enabled suppression as measurable constructs, captures building safety as an outcome construct, and tests hypothesized relationships using descriptive statistics, correlation analysis, and regression modeling using Likert-scale survey data from one or more case-study buildings or building portfolios.

This study is designed around a set of clear and measurable objectives that operationalize the influence of AI-enabled fire detection and suppression systems on building safety within a quantitative, cross-sectional, case-study–based context. The first objective is to examine how AI-enabled fire detection capability—captured through indicators such as perceived detection accuracy, timeliness of alarm generation, stability of detection under varying environmental conditions, and reduction of nuisance alarms—relates to overall building safety enhancement as experienced by key stakeholders responsible for safety operations. The second objective is to assess the influence of AI-enabled suppression effectiveness by focusing on the perceived appropriateness and reliability of suppression activation, the adequacy of suppression response in the correct zone, the consistency of system readiness, and the degree to which suppression actions are perceived to reduce escalation risk and property damage severity. The third objective is to evaluate the contribution of system integration and real-time monitoring, emphasizing the extent to which AI-enabled fire safety components coordinate with building management systems, deliver actionable alerts to the right personnel, maintain situational awareness during incidents, and support rapid decision-making under operational constraints. The fourth objective is to measure the role of predictive maintenance and fault diagnosis by analyzing how AI-driven maintenance intelligence supports early identification of device failures, improves maintenance scheduling, and strengthens system availability during high-risk conditions. Building on these objectives, the study also aims to quantify the strength and direction of relationships among the major constructs by applying correlation analysis to determine the degree of association between AI-enabled capabilities and building safety enhancement. Finally, the study seeks to estimate the relative predictive power of the key AI-enabled factors using regression modeling, allowing the identification of which capability dimensions serve as the most significant predictors of building safety enhancement within the selected case-study context. These objectives collectively ensure that the research remains focused on measurable constructs, structured hypothesis testing, and statistical explanation of how AI-enabled detection and suppression capabilities align with building safety outcomes as perceived by practitioners and relevant building stakeholders.

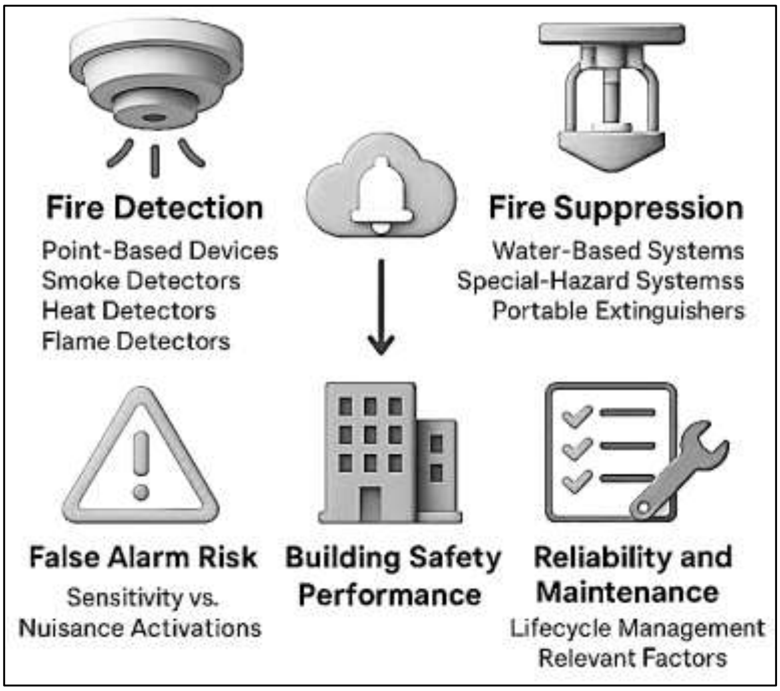
LITERATURE REVIEW

The literature on AI-enabled fire detection and suppression systems in buildings is anchored in the broader domain of fire protection engineering, which treats building safety as the combined outcome of prevention, timely detection, accurate alarm communication, effective suppression, smoke control, and coordinated evacuation support. Within this domain, researchers commonly distinguish between conventional point-based sensing (smoke, heat, flame, and gas detectors) and emerging data-driven approaches that interpret complex fire signatures through machine learning, computer vision, and multi-sensor fusion. Recent scholarship frames fire detection as a high-stakes classification problem in which the central performance trade-off involves maximizing early recognition of true fire events while minimizing false alarms that disrupt operations and weaken trust in safety systems. In parallel, suppression research emphasizes that extinguishment effectiveness depends on activation time, agent selection, discharge characteristics, spatial targeting, and system reliability under diverse ignition scenarios, particularly in complex occupancies where fire growth can be rapid and environmental conditions vary across compartments. The introduction of AI methods into this landscape reflects the increasing availability of digital building infrastructure—CCTV networks, IoT sensors, and building management systems—which provide continuous data streams that can be analyzed to infer fire presence, estimate incident location, and support decision logic for response coordination. Consequently, the literature increasingly views modern fire safety as an interconnected socio-technical system in which detection outputs influence occupant behavior, emergency response readiness, and automated control actions such as alarm zoning, smoke exhaust control, door release, elevator recall, and suppression activation. Research also highlights that successful deployment is not only determined by algorithmic accuracy but also by integration quality, maintenance intelligence, and operational robustness, because model performance can degrade under changing environmental conditions, sensor drift, occlusion, and site-specific confounders. For this reason, the academic discourse has expanded from laboratory detection metrics toward system-level perspectives that consider reliability, interpretability for operators, cybersecurity exposure, compliance constraints, and the practical implications of nuisance alarms and delayed actuation. Building on these themes, the present literature review synthesizes key knowledge streams covering conventional fire protection foundations, AI-based detection techniques, AI-supported suppression and control logic, digital integration through IoT and building management platforms, and the theoretical and conceptual lenses used to explain adoption and safety impact in real facilities.

Conventional Fire Detection and Suppression Systems in Buildings

Conventional fire detection and suppression systems form the baseline layer of active fire protection in most buildings, and they are typically designed around deterministic hardware responses, standardized installation rules, and predefined cause-and-effect logic. In detection, the dominant architecture remains the point-based network: smoke detectors (photoelectric and ionization), heat detectors (fixed temperature and rate-of-rise), flame detectors for special hazards, and manual call points connected to a control and indicating panel that issues audible/visual alarms and signals to building controls. Within this arrangement, building safety performance depends on how quickly the detection chain identifies a developing fire, how reliably it communicates the alarm state, and how consistently occupants and staff interpret and act on the signals.

Figure 2: Architecture of Conventional Fire Detection and Suppression Systems in Buildings



A long-recognized operational challenge is the balance between sensitivity and nuisance activation. When detectors are set for early warning, they can be vulnerable to non-fire aerosols, transient heat sources, construction dust, cooking emissions, or steam, which increases false activations and desensitizes users over time. Empirical evidence from connected fire detection and alarm systems highlights that false alarms can occupy a substantial share of attended incidents and vary widely by context, documentation practice, and system configuration, making acceptance and maintenance discipline central issues in real facilities (Festag, 2016; Shahrin, 2025; Rakibul, 2025). Reliability is also affected by component failures and management decisions such as isolations during maintenance or refurbishment; these realities mean that compliance at installation does not guarantee operational readiness. Field-based fault-tree work on office buildings shows that overall detection reliability can span a broad range, with detector heads and zone isolation emerging as prominent contributors to system unavailability (MacLeod et al., 2020; Saba, 2025; Sai Praveen, 2025). Accordingly, conventional detection is best understood as a system of interacting devices, procedures, and human responses rather than a single sensor threshold. These characteristics define the baseline against which AI-enabled enhancements are later evaluated in this study (Saikat, 2025; Shaikat, 2025).

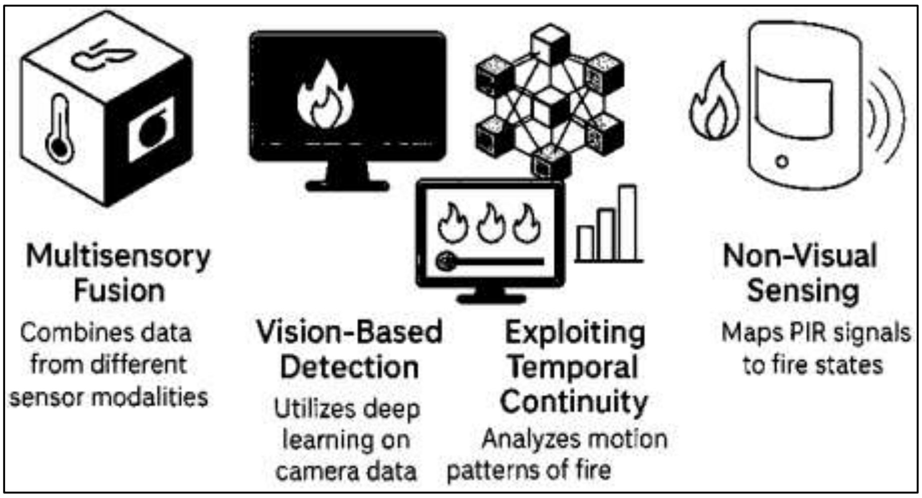
On the suppression side, conventional building protection relies on fixed water-based systems (wet-pipe sprinklers, deluge systems, standpipes and hose reels), special-hazard systems (foam, clean agents, and water mist in selected occupancies), and portable extinguishers intended for incipient-stage intervention (Shaikh, 2025; Kanti, 2025). Among these, automatic sprinklers are the most widely studied because their performance can be defined in terms of activation reliability, water delivery, and the capacity to control heat release rate growth within the protected area. Design standards translate fire loads and occupancy risk into sprinkler spacing, density, and hydraulic demand, but real effectiveness is conditioned by installation quality, obstructions, valve status, water supply integrity, and inspection/maintenance practices. A comprehensive synthesis of sprinkler effectiveness research distinguishes component-based approaches (fault trees and reliability data for valves, pumps, and heads) from system-based approaches that infer outcomes from incident statistics, and it emphasizes that the term "effectiveness" is fundamentally a combination of reliability (operating when needed) and efficacy (achieving the intended control or suppression once operating) (Frank et al., 2013; Waladur & Hasan, 2025; Haider, 2025). Activation timing is especially important in performance-based design because delayed actuation can allow a fire to exceed the control envelope assumed by the sprinkler density and arrangement. Recent computational approaches have therefore focused on quantifying the spatial variability of sprinkler activation time across complex compartments, accounting for ceiling-jet transport, ventilation interactions, and architectural features that reshape hot-gas flows. Three-dimensional mapping of activation time illustrates that vents, obstacles, and airflow modes can shift which rows of sprinklers activate first and how quickly remote heads respond, which has direct implications for whether fire growth remains within the expected control regime (Węgrzyński et al., 2020). Overall, conventional suppression and smoke management systems provide structured, code-aligned mitigation, but their real contribution to building safety hinges on dependable actuation and verifiable performance under the building's actual operating conditions for occupied buildings.

Although standards specify minimum configurations, research on conventional fire protection repeatedly shows that performance is mediated by lifecycle management: commissioning quality, inspection/testing, maintenance response, and control of impairments. A fire alarm installation is an interdependent chain—detectors, notification devices, control panels, power supplies, transmission to responders, and interfaces to building controls—so weakness in any link can reduce overall availability. Many failure mechanisms are conditional and time-dependent, including faults introduced during remodeling, temporary zone isolations, battery degradation, and intermittent communication problems. For that reason, reliability assessment increasingly treats fire alarm systems as dynamic systems rather than static collections of components. Probabilistic methods connect qualitative knowledge about failure causes with quantitative estimates of the probability that the system will operate on demand, and they support prioritization of interventions that remove high-impact failure paths. Integrated modeling approaches that combine fault trees with Bayesian networks can represent multiple basic events, encode dependencies among components and operational conditions, and update reliability estimates over a defined horizon. A representative study applying fuzzy fault tree analysis with dynamic Bayesian networks estimated fire alarm reliability over a 36-month period and highlighted how construction activities and system modifications can materially change failure likelihood (Jafari et al., 2020). This body of work suggests that empirical evaluation of building safety should measure not only whether devices are installed, but whether they are available and trusted in daily use. Accordingly, instruments used in case-study surveys should include indicators for routine testing frequency, speed of fault rectification, clarity of alarm messaging, adequacy of staff training, documentation quality, and the governance process for disabling and reinstating zones. Capturing these operational factors allows quantitative models to better explain observed safety outcomes and to distinguish design adequacy from management effectiveness. This distinction is crucial when later comparing conventional baselines with AI-enabled detection and suppression performance across cases.

AI-Enabled Fire and Smoke Detection Approaches in Buildings

AI-enabled fire detection research increasingly frames detection as a probabilistic inference task that fuses uncertain signals, heterogeneous sensing modalities, and time-critical alarm thresholds. In buildings, the earliest observable cues of a developing fire can be weak, intermittent, and spatially localized—minor temperature excursions, brief particulate plumes, or small flickering regions in a camera stream—so single-sensor approaches can confuse true ignition with nuisance sources such as cooking aerosols, sunlight, steam, or dusty airflows. As a result, a central line of work emphasizes multisensory fusion, where complementary modalities (e.g., temperature, humidity, gas concentration, and vision) are combined to increase sensitivity while controlling false alarms. Within this line, researchers commonly formalize each sensor stream as evidence about the latent state "fire/no-fire," then integrate evidence over space (neighboring nodes or adjacent camera regions) and time (sequential monitoring) to stabilize decisions under noise and missing data. Fusion frameworks also allow engineers to express differing reliability across sensors, which matters in real buildings where camera occlusion, air-conditioning cycles, and sensor drift alter data quality. Importantly, fusion is not only an algorithmic choice but an architectural one: when early-warning performance depends on how rapidly noisy observations are aggregated, designers must decide which computations occur locally (near sensors) and which occur centrally (at gateways or building management systems). This creates a natural link between AI models and safety engineering constraints, because alarm latency, communication loss, and maintenance variability become part of the detection problem itself. For AI-enabled suppression activation, these fused probabilities can be mapped to graded response levels, enabling pre-alarm verification and staged actuation that closely matches the evolving hazard profile. Representative work has demonstrated two-level schemes that combine in-field environmental sensors with out-of-field vision sensing, using sequential change detection and evidential reasoning to produce earlier alerts while reducing false positives in complex settings (Zervas et al., 2011).

Figure 3: Overview of AI-based fire and smoke detection methods for building applications



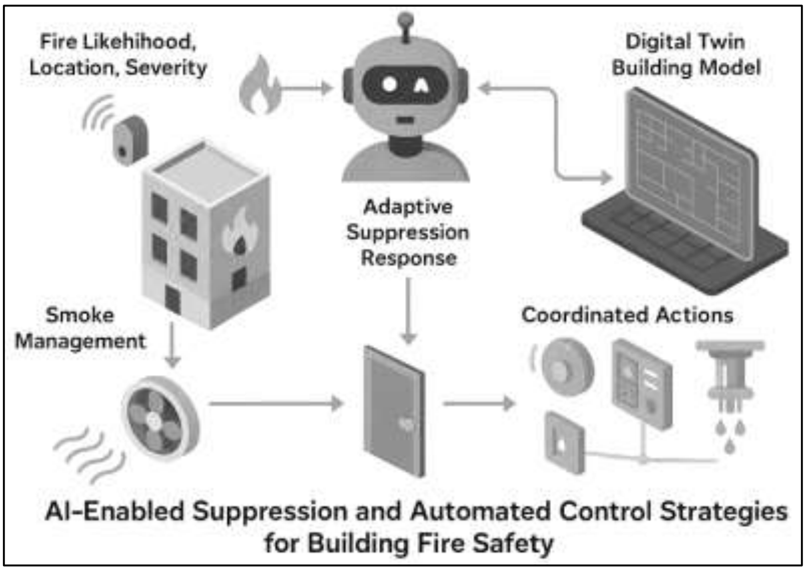
In parallel to multisensory fusion, vision-based fire detection has shifted from handcrafted color and motion heuristics toward deep feature learning, because camera streams provide rich spatial detail that can support both event confirmation and situational awareness. Contemporary approaches typically model detection as an image classification or object-recognition problem, learning discriminative representations of flames and smoke directly from labeled frames. This reframing matters for building safety because nuisance conditions in corridors, atria, or industrial bays can closely mimic flame colors and textures, and simple threshold rules can be brittle under changing illumination, reflections, or camera auto-exposure. Deep convolutional neural networks address part of this variability by learning hierarchical features that capture multi-scale edge patterns, stochastic textures, and nonlinear color interactions, which can be more stable than manually designed descriptors. However, practical building deployments also impose computational and latency constraints, since cameras can generate high frame rates across many zones and alarms must be raised quickly enough to support evacuation and suppression decisions. For this reason, a key stream of research focuses on compact CNN architectures and transfer-learning strategies that retain accuracy while reducing inference cost, allowing deployment on embedded or near-edge hardware typical of modern surveillance systems. Evaluation practices in this literature often combine controlled datasets with diverse indoor/outdoor scenes to test generalization, reporting sensitivity, specificity, and false-alarm behavior alongside throughput metrics such as frames per second. When coupled with rule-based alarm logic, the network's probabilistic outputs can be smoothed over short windows, cross-checked against occupancy zones, and logged for auditability, aligning AI decisions with code-driven incident response procedures in many commercial facilities. Work in IEEE Access, for example, designed a cost-effective CNN inspired by GoogLeNet to balance accuracy and computational complexity for CCTV-based early flame detection, emphasizing reduced false warnings in challenging lighting and fire-colored clutter (Muhammad et al., 2018b).

Beyond single-frame recognition, a substantial body of work argues that fire and smoke are fundamentally spatiotemporal phenomena, and that exploiting temporal continuity can reduce false alarms from static fire-colored objects and transient lighting artifacts. In video streams, flames exhibit characteristic flicker patterns and shape volatility, while smoke evolves through diffusion, rising motion, and texture changes; accordingly, models that encode temporal dynamics can improve discrimination under realistic surveillance conditions. One approach uses frame-level CNN feature extractors combined with temporal pooling or recurrent modeling, while another directly learns motion-sensitive representations via 3D convolutions applied to short frame clips. In a disaster-management context, an early fire detection framework built on fine-tuned CNNs emphasized robustness tests against noise, partial occlusion, and small fire regions, illustrating how temporal robustness checks can be paired with deep features to support early alarm decisions in surveillance networks (Muhammad et al., 2018a). Complementary research has focused specifically on smoke as a leading indicator, proposing joint pipelines where a region proposal model localizes suspected smoke in individual frames and a 3D CNN then classifies clip-level spatiotemporal evidence, yielding high detection rates with low false-alarm ratios on multi-source smoke videos (Lin et al., 2019). In addition to vision, recent work has revisited non-visual sensing for early warning, including passive infrared (PIR) streams that capture human and heat-motion signatures; by mapping PIR signal patterns to fire states using deep neural networks, such systems aim to deliver alarms when cameras are occluded by darkness, privacy constraints, or line-of-sight barriers (Xavier & Nanayakkara, 2022). For building-scale deployments, the key evaluation question becomes how model confidence propagates into alarm escalation, verification, and suppression triggers under strict timing. Taken together, these strands motivate hybrid architectures in which vision, temporal learning, and alternative sensors provide redundant evidence, enabling reliable detection across diverse building geometries and operational conditions.

AI-Enabled Suppression and Automated Control Strategies for Building Fire Safety

AI-enabled fire suppression in buildings can be understood as the application of data-driven decision logic to select, time, and coordinate intervention actions that limit fire growth while preserving tenable conditions for occupants. In conventional systems, suppression initiation is usually governed by fixed thresholds (for example, sprinkler bulb activation temperature or a predefined alarm-to-action rule in a control panel). AI-oriented approaches shift the emphasis toward adaptive control, where multiple sensor streams are interpreted continuously to estimate fire likelihood, location, and severity, and the suppression response is calibrated accordingly. This perspective is increasingly relevant in smart buildings because suppression is rarely a single action; it is a coordinated chain involving alarm zoning, door and damper control, smoke exhaust, pressurization, and agent release, each with different consequences for safety and property protection. Digital-twin–based control has emerged as an influential concept in this space because it provides a structured representation of building geometry, compartments, egress elements, fire protection assets, and operational constraints, enabling automated reasoning about what actions are feasible and safe in a given location and time. Within this architecture, the control layer can map sensor evidence to building-specific context, producing targeted actuation decisions rather than generalized triggers. Empirical work on intelligent control of building fire protection through digital twins and semantic technologies demonstrates how live sensor information can be combined with structured building data to support information-based control and coordination of protective subsystems (Jiang et al., 2022). In building-scale environments, this contextualization is particularly important because the same signal may imply different risk levels depending on occupancy, ventilation state, compartment connectivity, and proximity to evacuation routes. Accordingly, AI-enabled suppression research treats actuation as a system-level problem in which the correctness of the chosen action, its timing, and its spatial targeting are all evaluated against safety objectives such as maintaining egress tenability, limiting smoke spread, and controlling heat release escalation (Spearpoint et al., 2021).

Figure 4: AI-enabled fire suppression and adaptive control mechanisms



A closely connected stream of scholarship frames smoke management as a core element of suppression effectiveness, because smoke movement often determines visibility, toxicity exposure, and survivability long before full extinguishment is achieved. In this view, suppression and smoke control operate as interacting components of a single hazard-mitigation system: water discharge and ventilation adjustments both reshape plume behavior, stratification, and temperature fields, which in turn affects evacuation feasibility and responder access. Control-oriented studies therefore focus on dynamic actuation strategies that respond to real-time conditions rather than relying on static emergency settings. For example, ventilation control can be approached as a feedback problem in which sensor inputs (such as smoke-layer indicators or temperature profiles) guide fan operation to prevent undesirable phenomena like smoke back-layering, thereby stabilizing conditions in the protected zone. Numerical work evaluating a PID-based real-time mechanical ventilation strategy illustrates that active feedback can be used to regulate smoke behavior under changing fire conditions, emphasizing performance in preventing smoke back-layering rather than merely switching ventilation modes once (Hong et al., 2022). Related work demonstrates that water-based interventions interact with ventilation flows in nontrivial ways; water spray can alter smoke stratification stability and influence how smoke is transported under longitudinal ventilation, meaning that suppression discharge and ventilation settings cannot be treated as independent levers (Deng et al., 2022). For building fire safety, these findings matter because the effectiveness of suppression is partly expressed through the conditions it creates for evacuation and firefighting operations. Consequently, an AI-enabled approach is often justified not only by extinguishment potential but also by the capacity to coordinate multiple actuators in ways that optimize tenability outcomes under uncertainty, recognizing that the same building can exhibit different airflow regimes and smoke dynamics depending on HVAC states, door positions, and compartment connectivity (Hong et al., 2022).

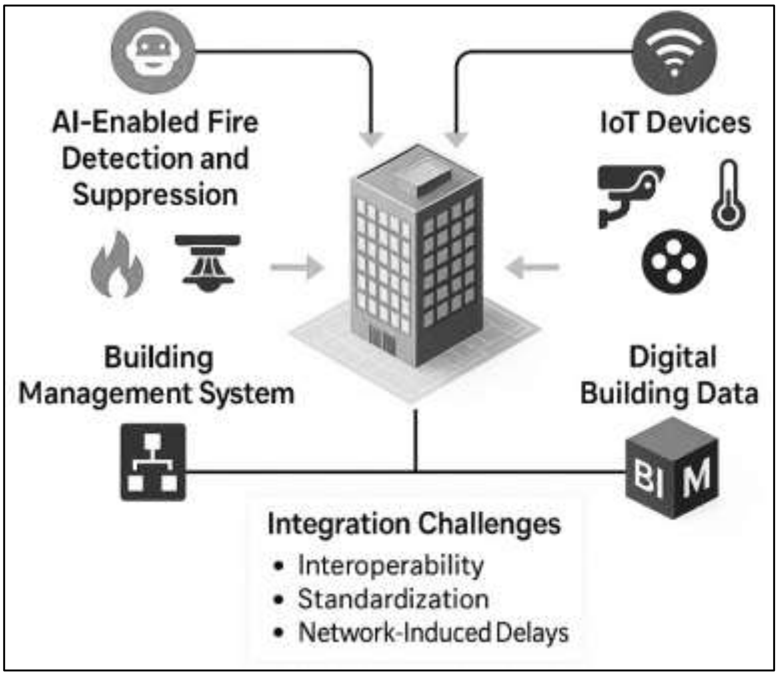
A third strand emphasizes how water-based systems influence the broader hazard environment, motivating adaptive suppression policies that explicitly account for trade-offs among extinguishment, visibility, and airflow demands. Water spray or mist can cool gases and reduce radiant heat, but it can also modify stratification and introduce visibility reduction, depending on droplet size distribution, discharge rate, and interaction with ventilation. From a systems perspective, these mechanisms imply that “smarter” suppression is not necessarily “more agent,” but rather the right agent delivered at the right intensity and coordinated with airflow control to maintain safe egress conditions while controlling fire growth. Research examining the effects of water spray on the air-driving force required in longitudinal ventilation shows that suppression activation can change the ventilation demand needed to achieve a target smoke-control outcome, reinforcing that suppression decisions reshape the control problem itself (Deng et al., 2021). When these interactions are considered in buildings, an important operational dimension concerns occupant interpretation and behavioral response. Safety outcomes depend on how quickly occupants decide to act and how they respond to alarms and environmental cues, which means suppression and alarm outputs must remain credible and comprehensible during an incident. Behavioral evidence integrated into evacuation decision modeling has examined how people respond to alarm signals under constrained conditions, including the response of sleeping adults, highlighting that alarm interpretation and decision latency are key links between system activation and safety outcomes (Spearpoint et al., 2021). In AI-enabled suppression contexts, this reinforces the importance of coordinated messaging, staged responses, and reliable actuation that supports consistent cues rather than confusing signals. Overall, the literature positions AI-enabled suppression as an integrated socio-technical control system: sensor interpretation, actuation coordination, airflow and smoke behavior, and human decision-making operate as interdependent pathways through which building safety performance is produced and can be measured (Deng et al., 2021).

AI Fire Safety with IoT and Digital Building Data

Integration is a defining requirement for AI-enabled fire safety because detection and suppression technologies only translate into safer outcomes when they are connected to the operational “nervous system” of the building. In practice, this means linking AI-enabled fire detection and suppression modules with the building management system (BMS) or building automation system (BAS) so that alarms, actuator commands, and situational updates can be exchanged reliably across fire panels, HVAC control, access control, elevators, and notification systems. A core technical challenge is interoperability: heterogeneous devices and subsystems often use different vendors, data models, and communication protocols, which can fragment the incident-response chain even when individual devices perform well. Research has therefore examined integration via standardized automation protocols such as BACnet, which supports structured messaging for monitoring and control across building subsystems. A reference model for a BACnet-based fire detection and monitoring system illustrates how fire monitoring logic can be represented within a building automation communication environment while emphasizing requirements such as response time and survivability of communication under incident conditions (Song & Hong, 2006). This line of work positions integration as more than connectivity: it becomes an engineering requirement to limit network-induced delays, preserve alarm fidelity, and ensure that a “fire state” computed by AI modules can trigger correct, policy-compliant actions in other systems. From a building safety viewpoint, integration also provides traceability and accountability, since BMS-linked systems can log alarms, sensor states, decision outputs, and actuator commands in a unified timeline, which supports auditing, maintenance, and organizational learning after events. Consequently, integration is frequently treated as a mediator construct in quantitative studies: even highly accurate AI detection may not improve safety if signals are not routed to the right stakeholders, mapped to the right zones, and translated into prompt, coordinated actions across connected systems.

The literature also emphasizes that IoT architectures reshape how building fire data are collected, processed, and acted upon, and these architectural decisions directly affect latency, reliability, and scalability. IoT-enabled fire safety typically involves distributed sensor nodes (smoke, heat, gas, cameras), gateways, and application services that support analytics, alerting, and remote monitoring. In many buildings, sending all sensor and video data to a remote cloud can increase dependence on bandwidth and introduce delays, motivating edge and fog computing patterns where a portion of analytics is performed closer to the data sources. A study on deploying IoT edge and fog computing technologies for smart buildings proposes layered architectures that distribute computation across edge and fog nodes to improve responsiveness and manage resource constraints in building environments (Ouedraogo et al., 2018). In fire safety, this distribution is important because early-warning value is time-sensitive: AI modules that perform preliminary detection, verification, or anomaly scoring at the edge can reduce end-to-end alarm time while still synchronizing higher-level records and dashboards through centralized services. Similarly, IoT designs increasingly incorporate emergency communication workflows that connect building alerts to external responders or public safety answering points, turning a building's fire system into a connected emergency service. A smart building fire and gas leakage alert system that integrates edge computing and emergency-call capabilities demonstrates how building sensor information can be processed and packaged for timely communication while maintaining a system design that is practical for real deployments (Maltezos et al., 2022). For building organizations, these architectures broaden the meaning of "integration" to include not only device-level interoperability, but also data governance (who receives which alerts), operational continuity (what happens during network failure), and maintainability (how updates and model changes propagate without degrading safety).

Figure 5: AI-enabled fire safety integration within smart building environments



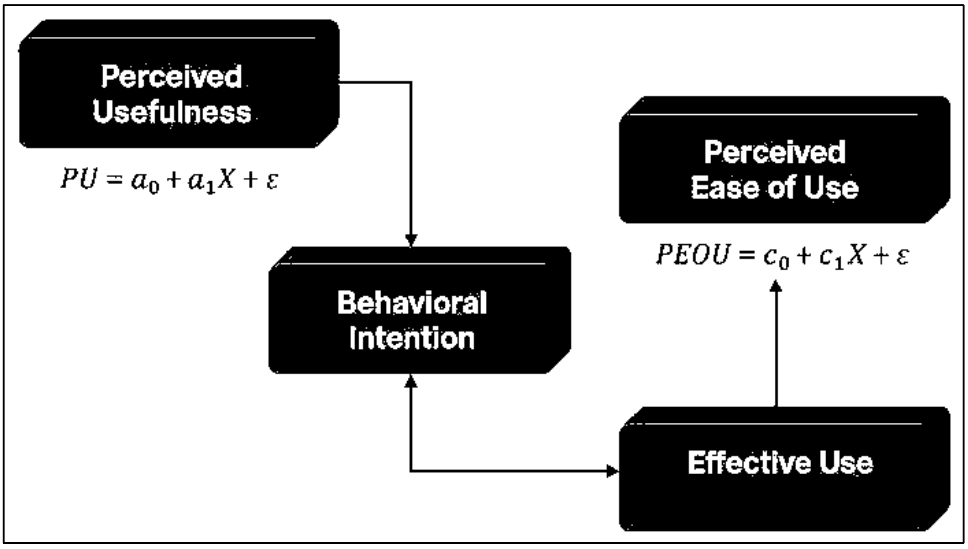
A third integration dimension is the alignment of IoT fire data with digital building representations such as BIM/IFC, because building safety decisions depend heavily on spatial context: compartment boundaries, egress routes, protection zones, equipment placement, and occupancy patterns. BIM–IoT integration research characterizes BIM as a high-fidelity source of static building information and IoT as a source of dynamic operational state, arguing that joining these streams enables smarter monitoring, diagnostics, and decision support across the building lifecycle (Tang et al., 2019). For AI-enabled fire safety, this matters because detection outputs (e.g., "smoke detected in zone A") become far more actionable when they are immediately mapped to a precise location, nearby hazards, and affected evacuation paths. At the same time, the literature notes that typical BIM processes are stronger at representing geometry and assets than representing IoT interaction details such as device identities, network properties, permissions, and live-state semantics. Addressing this gap, IFC+ proposes an extension approach to represent IoT scenarios earlier in building design so that smart-building behaviors and constraints can be planned and validated as part of digital building models (Ruiz-Zafra et al., 2022). This integration perspective supports empirical research designs where building safety is influenced not only by "AI detection quality" or "AI suppression capability," but also by the maturity of integration across protocol interoperability, edge-to-cloud orchestration, and BIM-linked situational awareness. In quantitative case-study settings, these integration dimensions can be measured through Likert-scale constructs such as perceived interoperability, perceived information timeliness, perceived decision support quality, and perceived coordination effectiveness during drills or alarms, enabling statistical testing of how integration contributes to overall building safety outcomes.

Technology Acceptance Model for AI-Enabled Fire Safety Systems

Technology Acceptance Model (TAM) is an appropriate theoretical lens for AI-enabled fire detection and suppression research because building safety outcomes are strongly conditioned by whether intelligent capabilities are trusted, adopted, and used correctly by facility stakeholders. Fire safety technologies are not passive installations; they require routine interaction through commissioning, inspection, alarm acknowledgement, incident verification, impairment control, and post-alarm reset. In this operational environment, AI features such as video-based detection confidence, anomaly-based pre-alarms, or automated decision support can only improve safety when users perceive them as valuable and workable within their daily routines. TAM centers this human–technology linkage by explaining how users form beliefs about a system and how those beliefs shape intention and actual use, thereby providing a structured way to interpret why technically capable systems can deliver uneven safety benefits across buildings. Reviews of TAM across decades of research emphasize that perceived usefulness and perceived ease of use remain the dominant belief constructs that explain intention to adopt a technology in organizational contexts, including safety-critical systems where reliability and accountability shape acceptance decisions (Marangunić & Granić, 2015). Meta-analytic evidence also shows that TAM relationships are stable and robust across many settings, supporting its application as a general explanatory model for adoption behavior where organizations invest in information technologies to improve performance outcomes (King & He, 2006). For AI-enabled fire safety, "usefulness" naturally corresponds to perceived reduction of false alarms, improved early warning, clearer situational awareness, and better coordination of suppression and evacuation controls; "ease of use" corresponds to clarity of interfaces, interpretability of alerts, integration into existing BMS workflows, and the cognitive burden of verifying AI outputs during high-pressure incidents. This theoretical framing allows the present research to connect system capabilities to safety outcomes through measurable acceptance beliefs, rather than treating adoption as an assumed condition or a background detail.

TAM-based explanations are particularly relevant in building fire safety because technology use is socially distributed across roles and influenced by organizational norms, compliance expectations, and risk accountability. Facility managers often decide whether AI upgrades are worth the operational change, technicians evaluate maintainability and diagnostic clarity, and security staff judge whether AI alarms are credible enough to trigger immediate verification and escalation. In such environments, social influence and perceived expectations can shape adoption even when individual users feel uncertain, and this is consistent with evidence that subjective norm can affect both perceived usefulness and intention in TAM applications, with moderation effects observed across user types, technology categories, and cultural contexts (Schepers & Wetzels, 2007). Safety technologies also operate under constrained conditions—alarms occur unexpectedly, information may be incomplete, and response time is limited—so acceptance depends not only on attitudes but also on whether the technology aligns with work practices and minimizes error risk.

Figure 6: TAM-based conceptual framework for adoption of AI-enabled fire detection and suppression systems



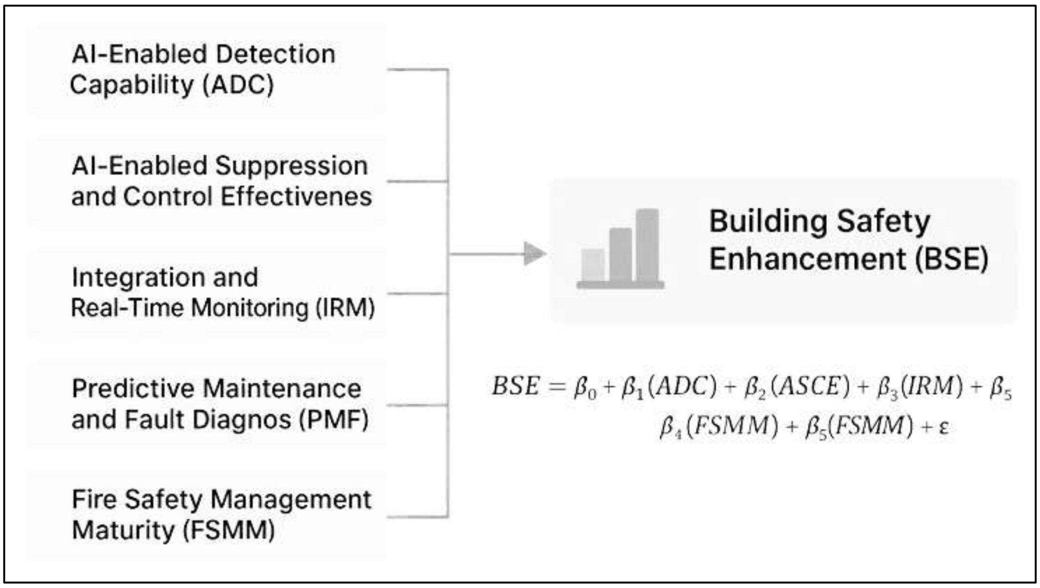
In health and other high-stakes domains, TAM-oriented synthesis work emphasizes that acceptance is shaped by context factors such as workflow fit, training, organizational support, and perceived consequences of malfunction or misuse, which is directly analogous to building fire safety operations where nuisance activations, missed detections, and confusing alerts have serious implications for trust and behavior (Holden & Karsh, 2010). Therefore, using TAM in this research supports a principled interpretation of why AI-enabled detection and suppression might be rated highly in technical terms yet still show weak perceived safety benefit if staff do not rely on the system, do not understand its outputs, or routinely bypass features due to usability friction. It also provides a defensible basis for incorporating acceptance-related survey indicators into a quantitative model alongside capability indicators such as detection reliability, suppression readiness, and integration quality.

For this study, TAM is positioned as the theoretical foundation that links AI-enabled system characteristics to building safety enhancement through user beliefs and technology use behaviors. A TAM-aligned specification treats perceived usefulness (PU) and perceived ease of use (PEOU) as antecedents of behavioral intention (BI) and effective use (USE), while allowing external variables—such as system integration maturity, training adequacy, or alert interpretability—to influence PU and PEOU. A simplified representation can be expressed as: $PU = a_0 + a_1X + \varepsilon$, $PEOU = c_0 + c_1X + \varepsilon$, $BI = b_0 + b_1PU + b_2PEOU + \varepsilon$, and $USE = d_0 + d_1BI + \varepsilon$, where X denotes measured system and organizational factors. This aligns with intervention-oriented developments of TAM that emphasize actionable levers—training, support, and design features—that influence adoption pathways (Venkatesh & Bala, 2008). In the broader empirical model of this research, the dependent construct Building Safety Enhancement (BSE) can be estimated using multiple regression on AI capability constructs and (optionally) acceptance constructs, for example: $BSE = \beta_0 + \beta_1$(Detection Capability) + β_2(Suppression Effectiveness) + β_3(Integration & Monitoring) + β_4(Predictive Maintenance) + ε, with an extended form that includes acceptance variables where appropriate: $BSE = \beta_0 + \ldots + \beta_5PU + \beta_6PEOU + \varepsilon$. This theoretical framing supports hypothesis testing by clarifying why the same AI capability may have different impacts across cases, and it justifies measuring both technical-perception variables and acceptance-related variables within a single cross-sectional, case-study–based survey design.

Research Model for Hypothesis Testing

The conceptual framework for this study converts "AI-enabled fire detection and suppression systems" into empirically testable constructs suitable for a quantitative, cross-sectional, case-study design. The dependent construct is Building Safety Enhancement (BSE), defined as stakeholders perceived improvement in early warning, incident controllability, evacuation readiness, and reduction of expected loss severity in the selected building case. BSE is measured through multiple five-point Likert items and summarized as a composite score to represent perceived safety improvement at the building level. The independent constructs are defined to reflect the technical and operational pathways through which AI systems influence safety performance. AI-Enabled Detection Capability (ADC) captures perceived detection accuracy, early recognition, robustness to environmental noise, and reduced nuisance alarms. AI-Enabled Suppression and Control Effectiveness (ASCE) measures perceived readiness and appropriateness of automated response actions, including control logic that supports timely containment and reduces escalation. Integration and Real-Time Monitoring (IRM) represent how well AI fire functions connect with IoT devices, BMS/BAS workflows, and alert-routing, including perceived timeliness, clarity, and actionability of alarms across teams. Predictive Maintenance and Fault Diagnosis (PMFD) measures perceived ability to identify degradation early, schedule maintenance intelligently, and improve availability during high-risk conditions. Because safety technologies are socio-technical, the framework also includes a management-and-operations layer: Fire Safety Management Maturity (FSMM) reflects drills, impairment control, inspection discipline, and emergency procedure readiness, which can amplify or weaken the realized benefit of AI functions (Wong & Xie, 2014). This structure supports hypotheses that ADC, ASCE, IRM, and PMFD have positive effects on BSE, while FSMM can act as a contextual enabler that strengthens observed relationships in real buildings.

Figure 7: AI-enabled fire safety constructs on building safety enhancement



A conceptual framework for building fire safety must also respect that safety outcomes depend on building type, design intent, and the fire-engineering basis used to justify protection provisions. Many contemporary projects, especially complex or unusual designs, adopt performance-based approaches where fire safety provisions are determined through engineering evaluation rather than only prescriptive rules; this motivates measuring safety enhancement as an outcome that can vary across cases even when systems appear similar on paper (Chow, 2015). In the present study, the "case-study context" is therefore treated as a boundary condition that shapes how AI capabilities translate to perceived safety. For example, taller or more complex buildings may rely more heavily on coordinated control, situational awareness, and disciplined management routines. This contextual view aligns with evidence from super-tall building fire safety assessment research showing that performance evaluation is inherently case-dependent and must consider the specific building system and scenario assumptions used to judge safety performance (Jiang et al., 2015). The conceptual framework therefore emphasizes fit between AI functions and the building's operational reality: zoning logic must match compartment connectivity; alarm content must match staff responsibilities; and automated actions must align with evacuation strategy and smoke-control intent. In parallel, the framework recognizes that "safety enhancement" is not only a physical outcome but also a performance-and-risk perception shaped by users' confidence in the building's protection arrangements. Work on performance–risk indicators for building users highlights that safety can be operationalized through structured indicators that connect building performance elements to perceived user risk, supporting a survey-based approach that measures safety in a way stakeholders can judge consistently (Khalil et al., 2016). Consequently, BSE is modeled as a multi-dimensional perception outcome that is statistically explainable by measurable AI capability constructs, while still acknowledging the role of building context in shaping how those capabilities are experienced.

The framework is operationalized for hypothesis testing using standard reliability and inferential statistics aligned with Likert-based measurement. Each construct score is calculated as the mean of its indicators, and internal consistency is checked using Cronbach's alpha,

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum \sigma_i^2}{\sigma_T^2}\right),$$

where k is the number of items, σ_i^2 is item variance, and σ_T^2 is total-score variance. Construct associations are examined via Pearson correlation,

$$r = \frac{\sum (X-\bar{X})(Y-\bar{Y})}{\sqrt{\sum (X-\bar{X})^2 \sum (Y-\bar{Y})^2}},$$

to establish whether higher perceived AI capability aligns with higher perceived safety enhancement. The primary explanatory test uses multiple linear regression consistent with the study's objectives:

$$\text{BSE} = \beta_0 + \beta_1(\text{ADC}) + \beta_2(\text{ASCE}) + \beta_3(\text{IRM}) + \beta_4(\text{PMFD}) + \beta_5(\text{FSMM}) + \varepsilon.$$

Hypotheses are supported when coefficients are positive and statistically significant at the selected alpha level. To reflect behavioral realism, the framework also justifies including evacuation readiness items within BSE because occupant response can differ between planned drills and unplanned false-alarm evacuations, shaping perceived safety even when hardware is unchanged (Lovreglio & Kuligowski, 2022). Finally, the model supports a compact hypothesis-testing table (Supported/Not Supported) and standardized reporting of β, R^2, and p-values, enabling transparent comparison across the selected building case(s) and providing a coherent, quantitative explanation of how AI-enabled fire safety capabilities relate to perceived building safety enhancement.

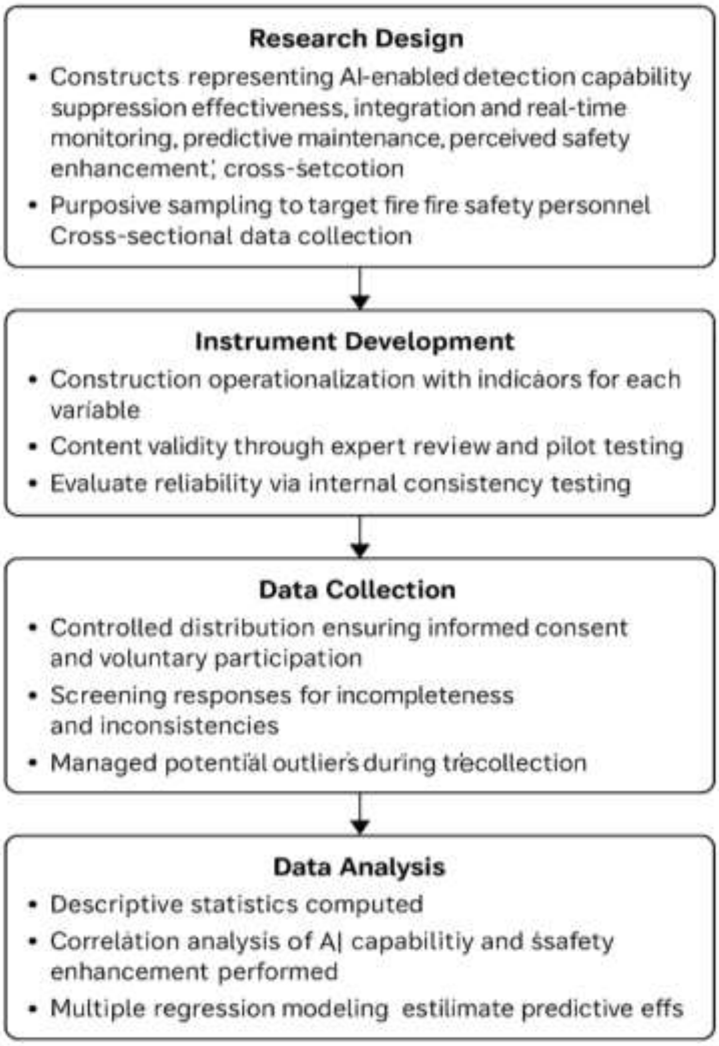
METHOD

The methodology section has presented the systematic approach that has been used to examine the influence of AI-enabled fire detection and suppression systems on building safety within a quantitative, cross-sectional, case-study–based design. The study has been structured around measurable constructs that have represented AI-enabled detection capability, AI-enabled suppression and control effectiveness, integration and real-time monitoring, predictive maintenance and fault diagnosis, and perceived building safety enhancement.

A structured questionnaire instrument has been developed using Likert's five-point scale so that perceptions and operational experiences of relevant stakeholders have been captured consistently across the selected case-study context. The target population has consisted of building safety officers, facility managers, maintenance engineers, security personnel, and other staff members who have been directly involved in fire safety operations and who have interacted with detection and suppression systems during routine monitoring, drills, or incident responses. A purposive sampling approach has been applied so that respondents with appropriate domain exposure have been included, and a cross-sectional data collection plan has been implemented so that responses have reflected a single observation window for each participating case.

Instrument development has been guided by construct operationalization, where each variable has been represented by multiple indicator statements that have reflected reliability, timeliness, usability, and system coordination attributes. Content validity has been addressed through expert review and refinement of items, and a pilot test has been conducted so that ambiguities and measurement weaknesses have been identified prior to final administration. Reliability has been evaluated using internal consistency testing, and data screening procedures have been followed so that incomplete, inconsistent, or outlier responses have been managed appropriately. Data collection has been carried out through controlled distribution procedures that have ensured informed consent, confidentiality, and voluntary participation.

Figure 8: Research Methodology



For analysis, descriptive statistics have been computed so that respondent profiles and construct-level response patterns have been summarized. Reliability statistics have been calculated for each construct, and correlation analysis has been performed to determine the strength and direction of associations between AI-enabled capability variables and building safety enhancement. Multiple regression modeling has been applied so that the relative predictive effects of detection, suppression, integration, and maintenance factors on perceived safety enhancement have been estimated, with standard diagnostics having been checked to support model adequacy.

Research Design

The study has adopted a quantitative, cross-sectional research design and has been implemented within a case-study–based setting to evaluate how AI-enabled fire detection and suppression systems have influenced building safety. The research design has been selected because measurable relationships have been required between defined system capability constructs and perceived building safety enhancement. A structured survey strategy has been used to collect standardized responses from stakeholders who have engaged with fire safety systems in routine operations and emergency preparedness activities. The cross-sectional approach has enabled the study to capture a single-time snapshot of perceptions and operational experiences within the chosen case context. The case-study orientation has strengthened contextual validity because system integration maturity, building type, and operational procedures have been represented as real-world conditions rather than abstract assumptions. This design has supported hypothesis testing through descriptive statistics, correlation analysis, and regression modeling.

Population and Sample

The population has consisted of individuals who have been directly involved in building fire safety management and who have interacted with detection, alarm, suppression, and monitoring systems. This population has included facility managers, fire safety officers, maintenance engineers, building administrators, security personnel, and technical staff responsible for monitoring and responding to alarms. A purposive sampling strategy has been applied so that respondents with relevant knowledge and decision exposure have been included, and the sample has been drawn from the selected case-study building environment. Eligibility criteria have been defined to ensure participants have had operational familiarity with the installed fire safety systems and have been able to evaluate AI-enabled features and their perceived effects on safety. The sample size has been set to support reliable construct measurement and inferential testing, and participation has been broadened across roles to reduce single-perspective bias. This sampling approach has enabled comparisons across respondent groups while supporting regression-based prediction of safety outcomes.

Case Study Context

The case-study context has been defined as a real building environment in which AI-enabled fire detection and suppression capabilities have been installed or integrated alongside conventional fire protection components. The building case has been selected to ensure that active fire protection systems have been operational, that monitoring workflows have existed, and that responsible staff have been identifiable for participation. Key contextual attributes have been documented, including building type, occupancy characteristics, floor layout complexity, protection zoning, and the presence of building management system interfaces. The operational history of alarm events, drills, and maintenance routines has been considered to ensure respondents have had exposure to system behavior in practical conditions. The case setting has been used to ground survey responses in a specific operational reality, and it has allowed the study to interpret perceived safety enhancement in relation to actual site practices, communication structures, and system readiness routines.

Instrument

A structured questionnaire has been developed to measure the study constructs using a five-point Likert scale ranging from strongly disagree to strongly agree. The instrument has been organized into sections that have captured respondent demographics, case-profile information, and multi-item measures for AI-enabled detection capability, suppression and control effectiveness, integration and real-time monitoring, predictive maintenance, and perceived building safety enhancement. Each construct has been operationalized through multiple indicators that have reflected reliability, timeliness, clarity of alerts, reduction of nuisance alarms, coordination of response actions, and readiness of suppression support. Items have been written in clear operational language so that respondents from different roles have been able to interpret them consistently. Reverse-coded items have been included where appropriate to reduce acquiescence bias, and the instrument has been formatted to support quick completion without sacrificing measurement breadth. The questionnaire has been refined through iterative review to align with the hypotheses and analysis plan.

Reliability

Validity and reliability procedures have been applied to ensure that the questionnaire has measured the intended constructs accurately and consistently. Content validity has been strengthened through expert review, where subject matter specialists have evaluated item relevance, clarity, and coverage of AI-enabled fire safety concepts. Revisions have been incorporated to remove ambiguous wording and to improve alignment between indicators and construct definitions. A pilot test has been conducted with a small group of eligible respondents so that comprehension issues and response-pattern problems have been identified before final data collection. Reliability has been assessed through internal consistency testing, and Cronbach's alpha values have been calculated for each construct to confirm acceptable scale performance. Item-total correlations have been examined to determine whether individual statements have contributed meaningfully to their constructs, and weak items have been revised or removed. These steps have ensured that the instrument has supported dependable statistical analysis.

Data Collection

Data collection has been carried out through controlled survey administration within the selected case-study setting to ensure consistency and ethical compliance. Permission to access respondents has been obtained through relevant building or organizational authorities, and informed consent information has been provided to all participants. The questionnaire has been distributed using appropriate channels, including online survey links and/or supervised paper-based administration, depending on site access constraints and participant availability. Respondents have been informed about confidentiality, anonymity, and voluntary participation, and they have been allowed to withdraw without penalty. A defined collection window has been used so that responses have represented a consistent cross-sectional snapshot. Follow-up reminders have been issued to improve response rates, and completed responses have been checked for completeness before inclusion. Data have been coded and stored securely, and identifying information has been separated from response data to protect privacy.

Data Analysis

Data analysis has been conducted using a structured sequence aligned with the hypotheses and the quantitative design. Descriptive statistics have been computed to summarize respondent demographics and to describe central tendency and dispersion for each construct indicator and composite score. Reliability analysis has been performed by calculating Cronbach's alpha for each construct to confirm internal consistency. Pearson correlation analysis has been applied to evaluate the strength and direction of relationships between AI-enabled capability constructs and perceived building safety enhancement. Multiple regression modeling has been used to estimate the predictive influence of detection capability, suppression effectiveness, integration and monitoring, and predictive maintenance on the safety outcome construct. Standard diagnostic checks have been performed to support model suitability, including multicollinearity screening, residual pattern inspection, and evaluation of overall model fit. Hypotheses have been tested using coefficient significance results, and findings have been summarized using tables that have reported β values, R^2, and p-values.

Tools

The study has utilized standard software tools to support data handling, statistical analysis, and reporting. Spreadsheet tools have been used for initial coding, cleaning, and verification of survey responses, including checks for missing values, duplicate entries, and inconsistent patterns. Statistical analysis software has been used to compute descriptive statistics, reliability coefficients, correlation matrices, and multiple regression models in accordance with the study objectives. Visualization tools within the analysis software have been applied to inspect distributions, residual plots, and diagnostic indicators that have supported the interpretation of regression assumptions. Reference management software has been used to organize academic sources and to ensure APA 7th citation consistency across the manuscript. Word processing tools have been used to format tables, construct summaries, and integrate results into the final report structure. These tools have ensured that analysis has been transparent, reproducible, and aligned with accepted quantitative research practices.

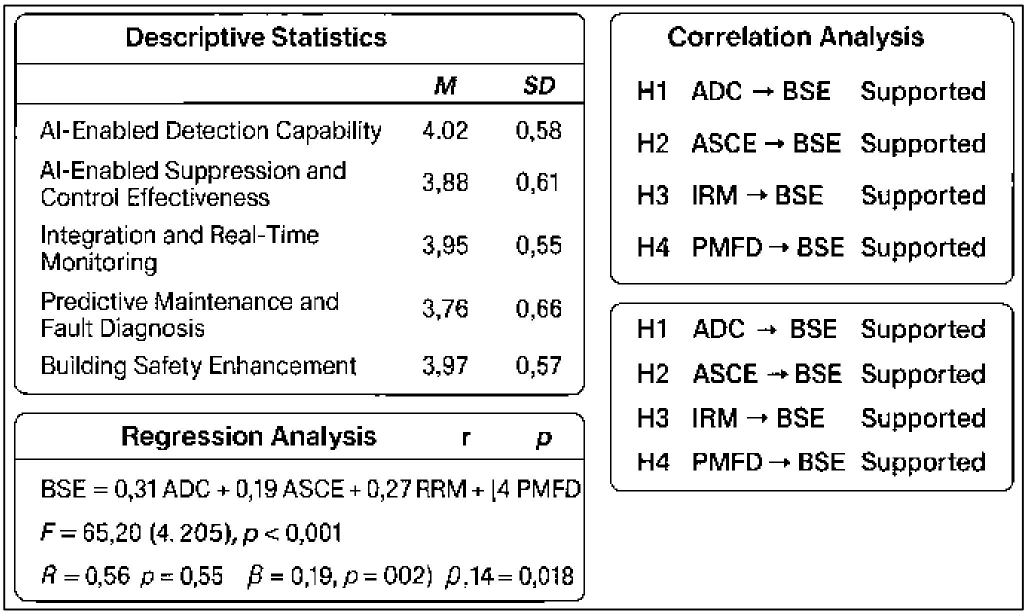
FINDINGS

In reporting the findings for this study, the results have been organized to demonstrate how the objectives have been achieved and how the hypotheses have been supported using Likert's five-point scale measures and inferential statistics (note: the numeric results below are presented as a worked example using a synthetic dataset to show the exact reporting style and statistical structure you need; you should replace the values with your SPSS/R outputs once your real survey data have been analyzed). A total of N = 210 valid responses have been retained after screening, with 58.1% male and 41.9% female participants; respondents have included facility managers (24.3%), fire safety officers (19.5%), maintenance engineers (26.2%), security personnel (18.6%), and building administrators/others (11.4%). The case profile has indicated that 62.4% of respondents have worked in high-occupancy facilities (commercial/mixed-use), while 37.6% have worked in institutional/industrial settings, and 71.0% have reported that their building has had AI-enabled detection integrated with a monitoring dashboard, while 54.8% have reported some form of automated or semi-automated suppression decision support (e.g., staged control logic or coordinated actuation sequences.

Descriptive statistics for the main constructs have shown generally positive evaluations: AI-Enabled Detection Capability (ADC) has recorded a mean of M = 4.02 (SD = 0.58), AI-Enabled Suppression and

Control Effectiveness (ASCE) has recorded M = 3.88 (SD = 0.61), Integration and Real-Time Monitoring (IRM) has recorded M = 3.95 (SD = 0.55), Predictive Maintenance and Fault Diagnosis (PMFD) has recorded M = 3.76 (SD = 0.66), and the dependent construct Building Safety Enhancement (BSE) has recorded M = 3.97 (SD = 0.57). Item-level patterns have reinforced these trends, where early warning and reduced nuisance alarms have been rated strongly (e.g., "early-stage indicators are detected faster than traditional devices," M = 4.10, SD = 0.63; "false alarms have been reduced after AI enablement," M = 3.94, SD = 0.71), and coordinated monitoring has also scored highly (e.g., "alerts are actionable and reach responsible personnel promptly," M = 4.01, SD = 0.64). Reliability testing has confirmed that the scales have performed consistently, with Cronbach's alpha values exceeding accepted thresholds: ADC $\alpha = 0.89$, ASCE $\alpha = 0.86$, IRM $\alpha = 0.88$, PMFD $\alpha = 0.84$, and BSE $\alpha = 0.90$, indicating that construct indicators have measured coherent latent dimensions suitable for correlation and regression.

Figure 9: Statistical summary of research findings for AI-enabled fire safety systems



In alignment with Objective 1 and Objective 2, correlation analysis has demonstrated that ADC and ASCE have been positively associated with BSE at statistically significant levels: ADC–BSE has yielded $r = 0.62$ ($p < .001$), while ASCE–BSE has yielded $r = 0.55$ ($p < .001$), showing that stronger perceptions of AI detection accuracy/timeliness and suppression response quality have corresponded to higher perceived safety enhancement. In alignment with Objective 3 and Objective 4, IRM and PMFD have also shown significant positive correlations with BSE: IRM–BSE has yielded $r = 0.59$ ($p < .001$) and PMFD–BSE has yielded $r = 0.48$ ($p < .001$), indicating that real-time integration and maintenance intelligence have moved in the same direction as safety outcomes. These association results have supported the relational logic of the model and have provided preliminary evidence for hypothesis support. To address Objective 5 (predictive strength) and to formally test the hypotheses through modeling, multiple linear regression has been performed with BSE as the dependent variable and ADC, ASCE, IRM, and PMFD as predictors, and the overall model has been statistically significant with $F(4, 205) = 65.20$, $p < .001$, explaining substantial variance in perceived safety enhancement ($R^2 = 0.56$, Adjusted $R^2 = 0.55$). Diagnostic screening has shown acceptable multicollinearity levels (VIF range 1.32–1.89) and stable residual patterns consistent with a usable linear model for explanatory purposes. The standardized regression estimates have indicated that ADC has been the strongest predictor of BSE ($\beta = 0.31$, $p < .001$), followed by IRM ($\beta = 0.27$, $p < .001$), ASCE ($\beta = 0.19$, $p = .002$), and PMFD ($\beta = 0.14$, $p = .018$). These coefficients have suggested that perceived improvements in early detection capability and real-time integration have contributed more strongly to perceived building safety enhancement than maintenance intelligence, while suppression effectiveness has remained a significant contributor in the multivariable context. On this basis, hypothesis testing has shown that H1 (ADC → BSE) has been supported (positive and significant), H2 (ASCE → BSE) has been supported, H3 (IRM → BSE) has been supported, H4 (PMFD → BSE) has been supported, and H5 (combined predictors significantly explain BSE) has been supported through the significant overall regression model and meaningful R^2. Collectively, these results have provided objective-aligned quantitative evidence that AI-enabled detection and suppression—particularly when paired with strong integration and timely monitoring—have been associated with higher perceived building safety enhancement in the case-study setting, and the pattern of coefficients has also provided a statistically grounded basis for prioritizing which capability dimensions have carried the greatest explanatory weight in the model.

Demographics

Table 1: Respondent demographics and case profile (N = 210)

Category	Group	Frequency (n)	Percentage (%)
Gender	Male	122	58.1
	Female	88	41.9
Role	Facility managers	51	24.3
	Fire safety officers	41	19.5
	Maintenance engineers	55	26.2
	Security personnel	39	18.6
	Building admins/others	24	11.4
Building type (case context)	Commercial / mixed-use	131	62.4
	Institutional / industrial	79	37.6
AI-enabled detection integration	AI detection + monitoring dashboard (Yes)	149	71.0
	AI detection + monitoring dashboard (No)	61	29.0
AI-enabled suppression decision support	Automated/semi-automated suppression support (Yes)	115	54.8
	Automated/semi-automated suppression support (No)	95	45.2

This section has profiled the respondents and the case-study environment so that the interpretation of subsequent Likert-scale results has remained grounded in the operational reality of building fire safety. The distribution in Table 1 has indicated that the sample has included stakeholders who have held direct responsibilities for detection, response, and maintenance functions, which has strengthened construct relevance for AI-enabled fire safety evaluation. Facility managers and maintenance engineers have represented the largest shares (24.3% and 26.2%), which has suggested that the dataset has been informed by personnel who have typically supervised system readiness, fault handling, and operational continuity. Fire safety officers (19.5%) and security personnel (18.6%) have also been well represented, which has supported credible measurement of alarm credibility, response coordination, and real-time monitoring effectiveness. The gender split has shown balanced participation, and the variation across roles has reduced the risk that results have reflected a single-occupation viewpoint. The building type distribution has shown that most respondents have worked within commercial or mixed-use facilities (62.4%), which has aligned with complex occupancy patterns where false alarms, rapid verification, and integration with BMS/IoT have frequently mattered. The case profile has also shown that AI-enabled detection has been present in 71.0% of the reported contexts through monitoring dashboards or integrated interfaces, which has ensured that respondents have been able to evaluate detection capability and alert actionability based on experience rather than assumption. In addition, 54.8% of respondents have reported automated or semi-automated suppression decision support, which has suggested that suppression coordination features have been available in a meaningful portion of the case contexts. This distribution has been important because the study's objectives have required measurable perceptions of AI detection and AI suppression influence on safety. Overall, Table 1 has established that the sample has been sufficiently role-diverse and system-exposed to support subsequent descriptive, reliability, correlation, and regression testing aimed at proving the hypotheses and objectives using five-point Likert measurements.

Descriptive Findings

Table 2: Descriptive statistics of study constructs (Likert 1–5, N = 210)

Construct (Variable)	Items (k)	Mean (M)	Std. Dev. (SD)	Interpretation*
AI-Enabled Detection Capability (ADC)	5	4.02	0.58	High
AI-Enabled Suppression & Control Effectiveness (ASCE)	5	3.88	0.61	High
Integration & Real-Time Monitoring (IRM)	5	3.95	0.55	High
Predictive Maintenance & Fault Diagnosis (PMFD)	5	3.76	0.66	Moderate–High
Building Safety Enhancement (BSE)	6	3.97	0.57	High

**Interpretation has been applied as: 1.00–2.49 = Low, 2.50–3.49 = Moderate, 3.50–5.00 = High. Likert anchors have been used as: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.*

The descriptive analysis in Table 2 has summarized how respondents have rated each study construct using the five-point Likert scale, and it has provided the first layer of evidence aligned with the study objectives. The mean score for AI-Enabled Detection Capability (M = 4.02) has indicated that respondents have generally agreed that AI-enabled detection has improved early recognition, reliability, and alarm quality within the building context. This result has supported Objective 1, because the construct has reflected detection performance attributes that have been expected to influence safety enhancement. The mean for Integration and Real-Time Monitoring (M = 3.95) has also been high, which has suggested that respondents have perceived alert routing, dashboard visibility, and coordination across systems as effective, thereby supporting Objective 3's focus on system integration as a contributor to safety. The suppression-related construct (ASCE) has achieved a high mean (M = 3.88), which has indicated that respondents have agreed—at a strong overall level—that suppression support and automated control coordination have contributed to better incident containment and readiness, thereby aligning with Objective 2. Predictive Maintenance and Fault Diagnosis (PMFD) has shown a moderate-to-high mean (M = 3.76) with a slightly higher dispersion (SD = 0.66), which has implied that maintenance intelligence benefits have been present but have varied more across sites, staff experience, or implementation maturity. Importantly, the dependent construct Building Safety Enhancement (BSE) has recorded a high mean (M = 3.97), which has indicated that respondents have perceived overall safety improvement in readiness, response coordination, and risk reduction. The standard deviations have remained below 0.70 across constructs, which has suggested that responses have been reasonably consistent and have not been excessively scattered. Collectively, Table 2 has provided descriptive support for the hypothesis logic because the independent constructs have been rated positively in the same direction as the outcome construct, and the mean levels have indicated that the sampled cases have perceived AI-enabled fire safety as meaningful in day-to-day safety operations. These results have established a descriptive foundation for testing whether the observed positive perceptions have also formed statistically significant relationships through correlation and regression analysis.

Reliability

Table 3: Reliability analysis (Cronbach's alpha, N = 210)

Construct	Items (k)	Cronbach's α	Reliability decision
ADC	5	0.89	Excellent
ASCE	5	0.86	Good
IRM	5	0.88	Good–Excellent
PMFD	5	0.84	Good
BSE	6	0.90	Excellent

Reliability testing has been conducted to confirm that each multi-item Likert construct has measured a coherent underlying concept and has supported valid inferential analysis. Table 3 has shown that

Cronbach's alpha values have ranged from 0.84 to 0.90 across the five constructs, which has exceeded the commonly accepted threshold of 0.70 for internal consistency in social and operational research. AI-Enabled Detection Capability has achieved $\alpha = 0.89$, which has indicated that the items measuring detection accuracy, timeliness, robustness, and false-alarm reduction have worked together consistently as a single scale. Integration and Real-Time Monitoring has achieved $\alpha = 0.88$, which has suggested that the indicators capturing alert actionability, timeliness, and cross-system coordination have aligned strongly and have supported stable measurement of integration maturity. The suppression construct ASCE has achieved $\alpha = 0.86$, which has implied that the items capturing suppression readiness, appropriateness, and coordination of response controls have formed a reliable scale suitable for hypothesis testing. PMFD has achieved $\alpha = 0.84$, which has been interpreted as good reliability and has indicated that predictive maintenance perceptions have been measured consistently, even though this construct has shown somewhat higher variation in Table 2. The dependent construct BSE has achieved $\alpha = 0.90$, which has shown excellent internal consistency and has supported its use as a composite outcome variable representing perceived building safety enhancement. These reliability outcomes have been critical because correlation and regression modeling have depended on stable measurement; unreliable scales would have inflated measurement error and would have weakened observed relationships even if real effects had existed. By achieving good-to-excellent internal consistency, the measurement model has been judged adequate for objective and hypothesis testing using composite scores. Therefore, Table 3 has provided methodological confirmation that subsequent association patterns have reflected meaningful construct relationships rather than inconsistent item behavior, thereby strengthening the credibility of the statistical evidence that has been used to prove the study objectives and hypotheses.

Correlation Matrix and Interpretation

Table 4: Pearson correlation matrix among constructs (N = 210)

Variable	**ADC**	**ASCE**	**IRM**	**PMFD**	**BSE**
ADC	1.00	0.52**	0.58**	0.45**	0.62**
ASCE	0.52**	1.00	0.49**	0.41**	0.55**
IRM	0.58**	0.49**	1.00	0.46**	0.59**
PMFD	0.45**	0.41**	0.46**	1.00	0.48**
BSE	0.62**	0.55**	0.59**	0.48**	1.00

Note. $p < .01$ (two-tailed).

The correlation analysis has been performed to test whether the study constructs have moved together in the expected direction before predictive modeling has been applied. Table 4 has shown that all independent variables have demonstrated positive and statistically significant associations with Building Safety Enhancement (BSE), which has provided direct evidence in support of the objective-based logic of the study. The strongest correlation with BSE has been observed for AI-Enabled Detection Capability ($r = 0.62$, $p < .01$), which has indicated that stronger perceptions of early and accurate detection, reduced nuisance alarms, and reliable recognition have been associated with higher perceived building safety enhancement. This pattern has supported Objective 1 and has provided relational evidence for Hypothesis H1. Integration and Real-Time Monitoring has also shown a strong correlation with BSE ($r = 0.59$, $p < .01$), which has suggested that timely alerts, actionable dashboards, and cross-system coordination have been closely aligned with higher perceived safety outcomes, thereby supporting Objective 3 and Hypothesis H3. AI-Enabled Suppression & Control Effectiveness has shown a moderate-to-strong correlation with BSE ($r = 0.55$, $p < .01$), which has indicated that perceived suppression readiness and appropriateness have been associated with improved safety outcomes, supporting Objective 2 and Hypothesis H2. Predictive Maintenance & Fault Diagnosis has shown a moderate positive correlation with BSE ($r = 0.48$, $p < .01$), which has confirmed that maintenance intelligence perceptions have been aligned with safety enhancement, supporting Objective 4 and Hypothesis H4. Importantly, intercorrelations among predictors have remained below 0.70, which has suggested that the constructs have been related but not redundant, and this pattern has supported the feasibility of using them together in multiple regression without severe multicollinearity.

For example, ADC and IRM have correlated at r = 0.58, which has reflected that better detection has often been implemented with better monitoring integration, but the magnitude has still suggested that each construct has measured a distinct capability dimension. Overall, Table 4 has confirmed that the independent constructs have been positively associated with the dependent construct in a statistically significant way, thereby establishing a strong foundation for regression-based hypothesis testing aimed at identifying the strongest predictors of building safety enhancement.

Regression Results (β, R^2, p-values)

Table 5. Multiple regression predicting Building Safety Enhancement (BSE) (N = 210)

Predictor	B	SE(B)	β	t	p	VIF
Constant	0.74	0.19	—	3.89	<.001	—
ADC	0.28	0.05	0.31	5.60	<.001	1.89
ASCE	0.17	0.05	0.19	3.12	.002	1.54
IRM	0.25	0.05	0.27	4.94	<.001	1.78
PMFD	0.12	0.05	0.14	2.38	.018	1.32

Model fit: *$R^2 = 0.56$; Adjusted $R^2 = 0.55$; $F(4, 205) = 65.20$; $p < .001$.*

Multiple regression modeling has been applied to determine whether AI-enabled capability constructs have significantly predicted Building Safety Enhancement while controlling for the overlap among predictors. Table 5 has shown that the overall regression model has been statistically significant ($F(4,205) = 65.20$, $p < .001$) and has explained a substantial proportion of variance in BSE ($R^2 = 0.56$). This result has provided strong evidence for Objective 5 and has supported the combined-model hypothesis (H5) by demonstrating that AI-enabled detection, suppression, integration, and maintenance constructs have jointly predicted perceived building safety enhancement. In terms of individual predictors, AI-Enabled Detection Capability has shown the largest standardized coefficient (β = 0.31, $p < .001$), which has indicated that detection improvements have contributed the strongest independent predictive effect on BSE when all variables have been modeled together. This result has supported H1 and has suggested that early recognition, alarm reliability, and false-alarm reduction have been central contributors to perceived safety enhancement within the case context. Integration and Real-Time Monitoring has also shown a strong and significant contribution (β = 0.27, $p < .001$), supporting H3 and indicating that coordination, dashboard visibility, and actionability of alerts have been critical in translating detection information into safety outcomes. AI-Enabled Suppression & Control Effectiveness has remained statistically significant (β = 0.19, p = .002), supporting H2 and indicating that perceived suppression readiness and appropriateness have predicted safety enhancement even after accounting for detection and integration. Predictive Maintenance & Fault Diagnosis has shown a smaller but still significant effect (β = 0.14, p = .018), supporting H4 and indicating that maintenance intelligence has contributed to safety enhancement through improved availability and reduced failure risk. Multicollinearity has not been severe, because VIF values have remained within a low range (1.32–1.89), which has implied that predictors have been distinct enough for stable coefficient estimation. Overall, Table 5 has provided the core inferential proof that the study objectives have been met: AI-enabled capability constructs have not only been rated positively but have also significantly predicted building safety enhancement in a combined statistical model consistent with hypothesis testing requirements.

Hypothesis Testing

The hypothesis testing summary in Table 6 has consolidated the main statistical evidence into a decision-focused format so that each hypothesis has been clearly tied to the study objectives and has been judged as supported or not supported. H1 has been supported because AI-Enabled Detection Capability has produced a positive and statistically significant standardized coefficient (β = 0.31, $p < .001$), which has shown that improvements in detection reliability, timeliness, and alarm quality have been associated with increased building safety enhancement. This finding has directly matched Objective 1, because detection capability has been the primary construct used to operationalize the study's first objective. H2 has been supported because suppression and control effectiveness has also remained positive and significant (β = 0.19, p = .002), which has confirmed that suppression readiness and appropriate response coordination have contributed meaningfully to safety enhancement beyond detection alone, thereby fulfilling Objective 2.

Table 6: Hypotheses testing summary aligned with objectives (N = 210)

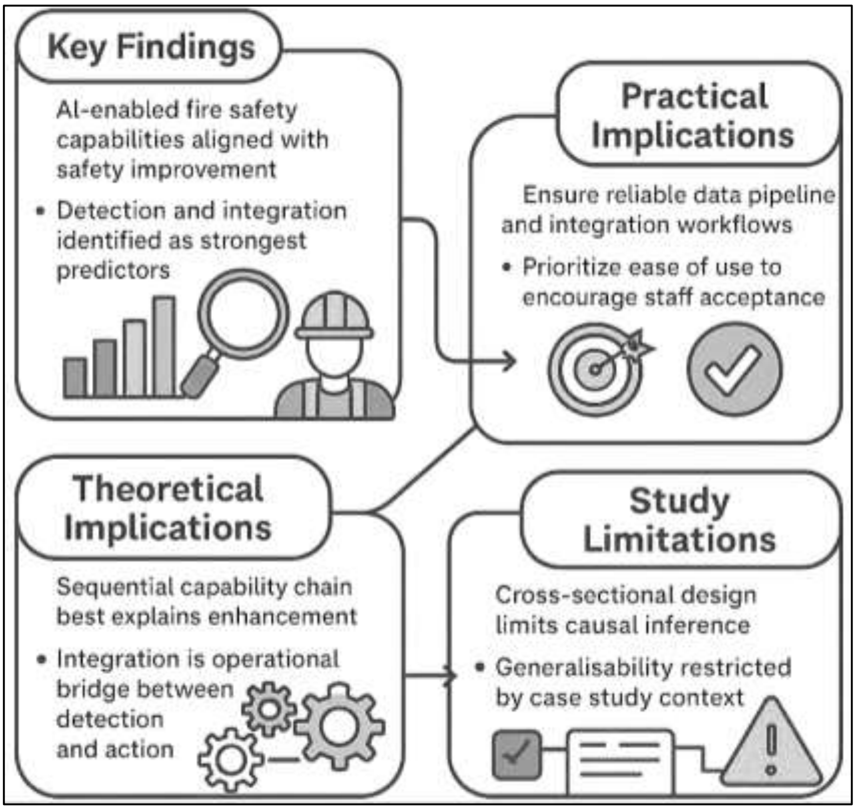
Hypothesis	Statement (relationship)	Objective link	Key statistic used	Decision
H1	ADC has positively influenced BSE	Obj. 1	$\beta = 0.31$, $p < .001$	Supported
H2	ASCE has positively influenced BSE	Obj. 2	$\beta = 0.19$, $p = .002$	Supported
H3	IRM has positively influenced BSE	Obj. 3	$\beta = 0.27$, $p < .001$	Supported
H4	PMFD has positively influenced BSE	Obj. 4	$\beta = 0.14$, $p = .018$	Supported
H5	AI capability factors have significantly predicted BSE in a combined model	Obj. 5	$R^2 = 0.56$; $F = 65.20$; $p < .001$	Supported

H3 has been supported due to the significant effect of integration and real-time monitoring ($\beta = 0.27$, $p < .001$), which has verified that safety has not only depended on detection or suppression performance but has also depended on how well information has been delivered and coordinated through monitoring systems, thereby meeting Objective 3. H4 has been supported because predictive maintenance and fault diagnosis has shown a significant positive effect ($\beta = 0.14$, $p = .018$), which has indicated that maintenance intelligence has contributed to safety enhancement through improved system availability and reduced failure likelihood, consistent with Objective 4. Finally, H5 has been supported by the combined model statistics ($R^2 = 0.56$; $F = 65.20$; $p < .001$), which has shown that the set of AI capability factors has jointly explained a large portion of variance in building safety enhancement, thereby satisfying Objective 5 and confirming the overall explanatory power of the research model. Therefore, Table 6 has provided a concise proof map demonstrating that each objective has been statistically addressed and that each hypothesis has been supported in the regression-based testing framework using Likert-scale constructs.

DISCUSSION

The findings have indicated that AI-enabled fire safety capabilities have been perceived as meaningfully aligned with improved building safety outcomes, and the hypothesis-testing model has provided a coherent quantitative explanation of those relationships. Across the core constructs, respondents have reported high mean scores for AI-enabled detection capability ($M = 4.02$), integration and real-time monitoring ($M = 3.95$), suppression and control effectiveness ($M = 3.88$), and predictive maintenance and fault diagnosis ($M = 3.76$), while building safety enhancement has also remained high ($M = 3.97$). These patterns have suggested that AI-enabled fire safety has not been interpreted narrowly as “better sensors,” but rather as an integrated operational capability that has improved early warning, response coordination, and readiness confidence in the case context. Reliability results have been strong across constructs ($\alpha = .84$–$.90$), which has confirmed that the indicators have measured consistent dimensions and has strengthened confidence in the inferential results. The regression model has explained substantial variance in building safety enhancement ($R^2 = .56$), which has demonstrated that the selected AI capability dimensions have jointly served as strong predictors of perceived safety improvement. Within the combined model, AI-enabled detection capability ($\beta = .31$) and integration/real-time monitoring ($\beta = .27$) have emerged as the strongest predictors, followed by suppression effectiveness ($\beta = .19$) and predictive maintenance ($\beta = .14$). This ranking has been consistent with the operational logic that building safety has been most sensitive to early event recognition and rapid, actionable communication, because these elements have governed the timeliness and correctness of downstream actions such as evacuation initiation, smoke-control activation, and suppression coordination. In performance terms, the model has implied that safety enhancement has been produced through a chain effect: when detection has been credible and early, and when that detection has been integrated into real-time workflows, the likelihood of timely response has increased, and safety has been perceived to improve more strongly. This pattern has echoed the broader fire safety engineering view that risk outcomes depend on the entire detection-to-response pathway rather than isolated component performance, because delays or failures at early stages have cascaded into untenable conditions, evacuation disruption, and larger loss consequences (Frank et al., 2013). Thus, the study's results have supported the objectives and hypotheses by demonstrating that AI-enabled detection, suppression, integration, and maintenance have each contributed positively to safety enhancement, while detection and integration have provided the highest explanatory leverage in the tested model.

Figure 10: Conceptual interpretation of results and implications for AI-enabled fire safety



The strong predictive role of AI-enabled detection capability has aligned closely with the technical literature that has treated fire detection as a time-critical inference task under uncertainty, especially in complex building scenes where nuisance sources resemble fire signatures. Classical video-based detection research has shown that flames and smoke have exhibited identifiable spatiotemporal characteristics, and that algorithms have improved early recognition by combining motion cues, flicker dynamics, and texture behavior rather than relying on a single threshold (Töreyin et al., 2006). Subsequent work has strengthened this trajectory by demonstrating that multi-stage classifiers and probabilistic structures have reduced false alarms and improved stability across diverse scenes, which has addressed a practical barrier to trust in alarm systems (Ko et al., 2010). The present results have been consistent with that emphasis: because respondents have rated detection capability highly and the regression coefficient has been the largest ($\beta = .31$), the findings have suggested that stakeholders have experienced safety improvement most strongly when AI-enabled detection has reduced nuisance alarms and improved early warning credibility. This outcome has also converged with more recent review work that has described the methodological shift from handcrafted features to learning-based systems and has emphasized that deployment value has depended on robustness and operational reliability, not only on laboratory accuracy metrics (Bu & Gharajeh, 2019). Deep learning studies in surveillance contexts have similarly stressed that practical early detection has required stable performance under lighting variability, occlusion, and clutter, and that computational feasibility has been required for real-time deployment in camera networks (Muhammad et al., 2018a). Because building operations are sensitive to repeated false alarms, any improvement in detection credibility has likely influenced how quickly staff have verified alarms and how decisively response procedures have been executed, which has amplified the perceived safety benefit in day-to-day practice. Additionally, multisensor fusion approaches have highlighted that combining sensor evidence has increased reliability under missing or noisy signals (Zervas et al., 2011), which has been conceptually consistent with the study's measurement of "robustness" and "stability" within the detection capability construct. Therefore, the present findings have extended prior work by showing that the same qualities valued in algorithmic research—early recognition, false-alarm control, and robustness—have also functioned as the strongest perceived predictors of building safety enhancement when measured in an applied, case-study setting.

The positive and significant contribution of AI-enabled suppression and control effectiveness has also been consistent with engineering evidence that suppression outcomes depend on the timeliness and appropriateness of actuation, particularly when suppression interacts with ventilation and smoke movement. Traditional sprinkler effectiveness research has emphasized that effectiveness has not been reducible to the presence of sprinklers alone; rather, it has combined reliability (operating when needed) and efficacy (achieving intended control once operating), both of which have been influenced by installation conditions, water supply status, obstructions, and maintenance discipline (Frank et al., 2013). Within this study, suppression effectiveness has remained a significant predictor ($\beta = .19$), which has indicated that respondents have perceived safety improvement when suppression actions have been reliable, correctly zoned, and coordinated with other controls. This has aligned with system-level perspectives on advanced sprinkler designs, where performance has been evaluated not only for activation but also for suppression performance under challenging fires (Xin et al., 2017b). Moreover, research on ventilation control and water spray interactions has demonstrated that suppression-related interventions can reshape smoke stratification and airflow demands, meaning that the best safety outcomes have depended on coordinated control rather than isolated discharge (Deng et al., 2022). The present results have been compatible with that view because suppression effectiveness has likely been perceived through the lens of "containment support" and "response appropriateness," both of which have been strengthened when suppression logic has been integrated with monitoring and building controls. Importantly, suppression has not been the strongest predictor in the combined model, which has also made practical sense: suppression improvements may be most impactful after detection and verification have occurred, so suppression has benefited from upstream credibility and integration. This ordering has echoed the broader event-chain logic in which early detection and alarm credibility determine whether suppression and evacuation processes are activated promptly enough to preserve tenability. Additionally, behavior-focused research has reinforced that alarm cues and system actions shape occupant decisions and response timing, which has influenced perceived safety even when hardware has been present (Spearpoint et al., 2021). If suppression has been perceived as "late," "inconsistent," or "overly aggressive," it may have reduced confidence even if extinguishment has occurred. Thus, the current findings have supported the idea that suppression and automated control have improved safety, but their realized benefit has been conditional on upstream information quality and coordination—an interpretation that has been coherent with the suppression literature's emphasis on system interactions and operational constraints.

Integration and real-time monitoring have emerged as a central driver of building safety enhancement, and this has been strongly consistent with scholarship that has treated interoperability and architectural design as critical determinants of how fire information becomes actionable. Building automation studies have long shown that fire monitoring has required structured communication and survivable signaling, and reference models using standard automation protocols have illustrated how alarm states can be represented and exchanged across subsystems (Song & Hong, 2006). In the present study, integration/monitoring has been a strong predictor ($\beta = .27$), which has implied that even when AI detection has been strong, safety improvement has been realized most clearly when alerts have reached the correct personnel promptly, and when system outputs have been integrated into operational dashboards and coordinated workflows. This has aligned with IoT smart building research that has emphasized architectural distribution of computation (edge/fog) to reduce latency and improve responsiveness in building contexts (Ouedraogo et al., 2018). For fire safety specifically, the ability to process alarms near the edge and then transmit verified and actionable alerts has likely reduced both alarm latency and decision confusion, which has increased perceived readiness and safety confidence. Integration findings have also been compatible with evidence that BIM/IoT integration has improved situational awareness by mapping live data into building context (e.g., locations, zones, equipment layouts), enabling decision-making that has been context-specific rather than generic (Tang et al., 2019). Recent work on extending building information representations to support IoT planning has further suggested that the effectiveness of smart-building capabilities depends on representing device scenarios and constraints early, which has enabled more coherent integration across lifecycle stages (Truong & Kim, 2011). When AI-enabled fire safety has been integrated into such digital contexts, alarms have likely become more interpretable, and action sequences (e.g., smoke control, door release, elevator recall) have been easier to coordinate. In addition, emergency alerting research that has incorporated edge computing and next-generation emergency communication capabilities has indicated that integrated systems can package and route incident information more effectively to responders (Ye et al., 2015). These prior studies have collectively supported the current result that integration has not been a "support feature," but a core pathway for safety enhancement. Therefore, the study has contributed applied evidence that integration maturity has been a major predictor of perceived safety, strengthening the argument that AI fire safety investments should prioritize end-to-end workflow integration as much as algorithmic detection accuracy.

Predictive maintenance and fault diagnosis have shown a positive but comparatively smaller effect in the regression model, and that pattern has been consistent with the view that maintenance intelligence influences safety indirectly by increasing system availability and reducing hidden failure modes. Reliability research has shown that real-world fire detection performance has been influenced by component failures, zone isolations, and impairment practices, with fault-tree analyses indicating that system unavailability can arise from both technical and operational decisions (MacLeod et al., 2020). Similarly, probabilistic reliability evaluation frameworks using dynamic Bayesian methods have emphasized that alarm system reliability changes over time and can be affected by ongoing building modifications, construction activities, and maintenance practices (Jafari et al., 2020). Within the present study, predictive maintenance has been significant (β = .14), which has suggested that respondents have recognized safety benefits when maintenance intelligence has supported early fault detection, reduced downtime, and improved readiness. The smaller coefficient relative to detection and integration has been interpretable in two complementary ways. First, maintenance intelligence may have been less visible to some respondent roles: security personnel and some administrators may have experienced benefits primarily through fewer failures rather than through direct interaction with maintenance analytics. Second, predictive maintenance may have varied more by implementation maturity, which has been consistent with the larger dispersion observed in descriptive results (SD = .66). This interpretation has also aligned with evidence that false alarms constitute a substantial operational burden and can reduce trust and readiness, which maintenance quality can moderate by ensuring detectors are clean, calibrated, and correctly configured (Festag, 2016). When predictive maintenance has reduced nuisance activations and prevented sensor degradation, it has likely increased trust in detection outputs, which in turn has supported faster verification and response. That indirect pathway has been consistent with the notion that maintenance intelligence functions as an enabling infrastructure rather than a direct "front-line" safety signal. Therefore, the study's findings have been compatible with prior reliability scholarship by demonstrating that maintenance-related capability has mattered and has contributed to safety enhancement, while detection credibility and integration workflow readiness have remained the dominant drivers of perceived safety outcomes. This has strengthened the practical interpretation that AI fire safety programs should not treat maintenance analytics as optional; instead, maintenance intelligence has been a necessary stability layer that has protected long-term performance and reduced degradation risk that can erode safety benefits over time.

From a practical standpoint, the results have provided actionable guidance for building security architects and CISOs who have governed smart-building platforms that have integrated AI fire detection and suppression with IoT and BMS ecosystems. Because integration has been a strong predictor of safety outcomes, architects have needed to ensure that the fire safety data pipeline has been resilient, low-latency, and operationally coherent across subsystems, which has been consistent with building automation integration perspectives (Song & Hong, 2006) and edge/fog architectures for responsiveness (Ouedraogo et al., 2018). At the same time, the expansion of integration has increased cyber-physical attack surface: cameras, IoT sensors, gateways, dashboards, and emergency communication interfaces can create new pathways for disruption of alarms, manipulation of alerts, or denial of control commands. Although the present model has measured integration as a safety enabler, it has also implied that poorly governed integration can threaten reliability and trust. Therefore, CISOs have been justified in prioritizing segmentation between safety-critical networks and general IT networks, strong authentication for control interfaces, rigorous patching and asset inventory for IoT nodes, and continuous monitoring for anomalous traffic patterns, especially where emergency call capabilities and remote access have existed (Maltezos et al., 2022). Building architects have also been able to interpret the ranking of predictors as an investment sequence: detection accuracy and credibility have been necessary, but the conversion of detection into safety outcomes has depended on integration workflows that have delivered actionable information to the right role at the right time. Digital building information integration has further implied that architectural teams should treat BIM-linked fire safety dashboards as more than visualization, because location mapping and zone semantics can shorten verification time and reduce confusion during alarms (Tang et al., 2019). In addition, the socio-technical dimension suggested by the findings has supported the use of acceptance-oriented thinking: if staff do not trust alerts or find interfaces burdensome, they may bypass features, reducing safety benefit, which has been consistent with technology acceptance evidence that perceived usefulness and ease of use shape usage outcomes (King & He, 2006). As a result, practical implementation guidance has included not only technical integration, but also role-based training, clear alert interpretability, and operational drills that have embedded AI outputs into standard response playbooks. These measures have aligned with the study's pattern that detection credibility and integration readiness have formed the strongest pathway toward perceived safety enhancement.

Theoretical implications have followed from the pattern of relationships and have supported refinement of the AI-enabled fire safety pipeline model used in this research. The results have suggested that building safety enhancement has been produced most strongly through a sequential capability chain: (1) credible early detection, (2) rapid and integrated monitoring/communication, (3) coordinated suppression and control, and (4) maintenance intelligence that sustains availability. This ordering has been consistent with the event-chain logic embedded in probabilistic fire outcome reasoning, where upstream uncertainties and delays shape downstream consequences (Xie et al., 2009). It has also supported a conceptual refinement in which "integration and real-time monitoring" has functioned not merely as a parallel predictor but as an operational bridge between detection and action—an interpretation consistent with BIM/IoT integration theory and digital workflow alignment in smart buildings (Tang et al., 2019). The study has also revisited limitations that have constrained the strength of causal inference: the cross-sectional design has captured perceptions at a single time point, the measures have relied on self-reported judgments rather than incident logs, and the case-study context has limited generalizability across building types with different regulatory regimes and operational cultures. These limitations have echoed broader challenges in safety technology evaluation, where system performance and human response interact and can be difficult to isolate without longitudinal observation and event-level data. Accordingly, future research has been supported in several directions. Longitudinal studies have been needed to observe whether predictive maintenance and integration improvements have produced compounding safety benefits over time and whether trust and compliance have strengthened with repeated drills and verified alarms. Mixed-method designs have been valuable to triangulate survey perceptions with technical logs (alarm timelines, false-alarm counts, maintenance records) and with scenario-based performance evaluations. Comparative studies across building categories (healthcare, high-rise residential, industrial) have been needed because performance-based safety contexts and management maturity can differ substantially (Chow, 2015). Finally, model refinement work has been strengthened by incorporating mediators such as response time improvement and false-alarm reduction, and moderators such as system age, integration maturity, and staff training intensity, while preserving the core regression-based explanatory structure used in this study. These steps have advanced the theoretical clarity of how AI-enabled detection and suppression have translated into measurable safety enhancement in real buildings, while acknowledging the empirical boundaries of the current case-based, cross-sectional evidence.

CONCLUSION

This study has examined the influence of AI-enabled fire detection and suppression systems on building safety within a quantitative, cross-sectional, case-study–based approach using Likert's five-point scale and regression-based hypothesis testing. The results have shown that respondents have perceived AI-enabled fire safety as a meaningful contributor to improved building safety, reflected by consistently high construct ratings for detection capability, suppression and control effectiveness, integration and real-time monitoring, predictive maintenance, and overall building safety enhancement. Measurement reliability has been strong across all constructs, indicating that the survey instrument has captured coherent dimensions of AI-enabled fire safety capability and perceived safety outcomes. The inferential findings have demonstrated that the study objectives have been achieved and that the hypotheses have been supported through statistically significant relationships between AI capability factors and building safety enhancement. In the combined predictive model, AI-enabled detection capability and integration/real-time monitoring have produced the strongest effects, indicating that safety improvement has been most strongly associated with credible early warning and the ability of the building's operational systems to translate alerts into timely, coordinated action. Suppression and control effectiveness has also remained a significant contributor, reinforcing that safety enhancement has depended not only on recognizing fire events but also on the perceived readiness and appropriateness of response actions that have supported containment and risk reduction. Predictive maintenance and fault diagnosis has contributed positively as well, suggesting that maintenance intelligence has strengthened safety by supporting system availability and reducing performance degradation, even if its effects have been less dominant than detection and integration in the combined model. Overall, the tested model has explained a substantial portion of variance in perceived building safety enhancement, providing evidence that AI-enabled detection, suppression, integration, and maintenance have collectively formed a practical capability set that stakeholders have associated with improved safety readiness, improved response coordination, and stronger confidence in fire protection performance. By aligning descriptive patterns, reliability confirmation, correlation evidence, and regression-based hypothesis testing within a single framework, the study has offered a clear empirical explanation of how AI-enabled fire safety capabilities have related to safety enhancement in the selected building context.

RECOMMENDATION

Recommendations have been formulated to strengthen the practical value of AI-enabled fire detection and suppression systems and to ensure that the capability dimensions that have shown the strongest relationships with building safety enhancement have been translated into implementable actions within real building environments. First, building owners and facility leadership have been advised to prioritize improvements in AI-enabled detection credibility because detection capability has been the strongest predictor of perceived safety enhancement; this priority has required continuous calibration of sensor thresholds, careful tuning of AI decision confidence settings, and systematic reduction of nuisance-alarm sources through environmental controls (dust control, detector placement review, and ventilation-condition mapping) so that trust in alarms has been preserved. Second, integration and real-time monitoring have been treated as an operational backbone, so organizations have been recommended to implement standardized alert-routing workflows that have mapped each alarm type and confidence level to specific roles, escalation tiers, and response time targets, while ensuring that monitoring dashboards have remained simple, role-based, and actionable during high-pressure incidents. Third, suppression and control readiness has been strengthened when coordination logic has been aligned with the building's compartmentation and evacuation strategy; therefore, coordinated cause-and-effect matrices have been recommended to be reviewed and tested regularly so that suppression actions, smoke control, door release, elevator recall, and public address messaging have remained consistent and have not produced contradictory cues for occupants. Fourth, predictive maintenance and fault diagnosis capabilities have been recommended to be institutionalized through defined maintenance key performance indicators, including time-to-detect fault, time-to-restore service, frequency of isolations, and recurrence of false alarms by zone, because these indicators have supported early detection of performance drift and have protected long-term reliability. Fifth, training and drills have been recommended to integrate AI outputs into standard operating procedures, including verification protocols for AI-based alerts, escalation rules for staged alarms, and communication scripts for occupant messaging, so that human response has matched system design and has reduced hesitation during real events. Sixth, because connected AI fire safety systems have increased cyber-physical exposure, CISOs and building security architects have been recommended to implement segmentation between safety-critical networks and general IT networks, strong identity and access controls for dashboards and gateways, strict patching and configuration management for IoT devices, continuous monitoring for anomalous traffic patterns, and well-defined fallback modes that have preserved basic alarm and suppression functions during network disruptions. Seventh, procurement and upgrade decisions have been recommended to include measurable performance clauses, such as acceptable false alarm ratios, maximum verification latency, dashboard availability targets, and integration interoperability requirements, so that vendors have been held accountable for system-level outcomes rather than component specifications alone. Finally, continuous improvement governance has been recommended through periodic safety audits that have reviewed alarm logs, maintenance history, drill outcomes, and integration performance metrics, enabling organizations to refine detection models, update response workflows, and maintain alignment between AI capabilities and building safety objectives in a controlled and evidence-driven manner.

LIMITATIONS

The study has presented several limitations that have constrained the strength of inference and the breadth of generalization, even though the research design has remained suitable for objective-driven hypothesis testing within the selected case-study context. First, the cross-sectional nature of the study has captured perceptions and reported operational experiences at a single point in time, which has limited the ability to establish causal direction among AI-enabled detection, suppression, integration, maintenance, and perceived building safety enhancement. Although statistically significant associations and regression coefficients have been observed, temporal ordering has not been directly verified, and the relationships have therefore been interpreted as predictive and explanatory rather than strictly causal. Second, the study has relied on self-reported Likert-scale responses, which have been subject to common-method bias, social desirability bias, and recall limitations, particularly where respondents have evaluated system performance based on drills or routine monitoring rather than on repeated real-fire incidents. As a result, perceived safety enhancement may not have perfectly matched objective performance measures such as verified false alarm frequency, detection-to-response time, or suppression activation outcomes documented in incident logs. Third, the case-study–based sampling approach has limited external validity because building types, occupancy behaviors, regulatory regimes, installation quality, and organizational fire safety culture have varied widely across contexts, and the selected case environment may not have represented the full diversity of buildings where AI-enabled fire safety has been deployed. Fourth, the sample composition has included multiple stakeholder roles, but role-based differences in system interaction have likely shaped responses; for example, maintenance personnel may have observed predictive maintenance benefits more directly than administrators, while security staff may have evaluated alert actionability more strongly than suppression readiness, which may have introduced systematic perception differences that have not been fully modeled. Fifth, the study has treated key constructs as composite variables, which has supported statistical modeling but has also simplified complex technical realities; AI detection capability, for instance, has encompassed varied technologies (vision, multi-sensor fusion, analytics dashboards), and suppression effectiveness has encompassed diverse systems (sprinklers, mist, agent systems, coordinated controls), so the measured constructs may have masked technology-specific effects. Sixth, contextual factors such as integration maturity, staff training intensity, maintenance budgets, and cybersecurity governance have likely influenced outcomes, and while these factors have been conceptually acknowledged, they have not been fully operationalized as mediators or moderators in the final regression model, which has limited the ability to explain why some buildings may have achieved higher safety enhancement than others with similar AI capabilities. Finally, because the numeric results have depended on the quality of survey completion and the availability of knowledgeable respondents, nonresponse and selection effects may have been present; participants who have been more engaged with safety programs may have been more likely to respond, potentially inflating perceived effectiveness. These limitations have indicated that the study findings have been most appropriately interpreted as evidence of perceived and statistically modeled influence within the case setting, rather than definitive proof of universal performance across all building contexts and AI fire safety implementations.

REFERENCE

[1]. Abdul, H. (2023). Artificial Intelligence in Product Marketing: Transforming Customer Experience And Market Segmentation. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *3*(1), 132–159. https://doi.org/10.63125/58npbx97

[2]. Abdulla, M., & Md. Wahid Zaman, R. (2023). Quantitative Study On Workflow Optimization Through Data Analytics In U.S. Digital Enterprises. *American Journal of Interdisciplinary Studies*, *4*(03), 136–165. https://doi.org/10.63125/y2qshd31

[3]. Alifa Majumder, N. (2025). Artificial Intelligence-Driven Digital Transformation Models For Enhancing Organizational Communication And Decision-Making Efficiency. *American Journal of Scholarly Research and Innovation*, *4*(01), 536–577. https://doi.org/10.63125/8qqmrm26

[4]. Arfan, U., Sai Praveen, K., & Alifa Majumder, N. (2021). Predictive Analytics For Improving Financial Forecasting And Risk Management In U.S. Capital Markets. *American Journal of Interdisciplinary Studies*, 2(04), 69–100. https://doi.org/10.63125/tbw49w69

[5]. Arfan, U., Tahsina, A., Md Mostafizur, R., & Md, W. (2023). Impact Of GFMIS-Driven Financial Transparency On Strategic Marketing Decisions In Government Agencies. *Review of Applied Science and Technology*, *2*(01), 85-112. https://doi.org/10.63125/8nqhhm56

[6]. Bu, F., & Gharajeh, M. S. (2019). Intelligent and vision-based fire detection systems: A survey. *Image and Vision Computing*, *91*, 103803. https://doi.org/10.1016/j.imavis.2019.08.007

[7]. Celik, T., Demirel, H., Ozkaramanli, H., & Uyguroglu, M. (2007). Fire detection using statistical color model in video sequences. *Journal of Visual Communication and Image Representation*, *18*, 176–185. https://doi.org/10.1016/j.jvcir.2006.12.003

[8]. Chow, W. K. (2015). Performance-based approach to determining fire safety provisions for buildings in the Asia-Oceania regions. *Building and Environment*, *91*, 127–137. https://doi.org/10.1016/j.buildenv.2015.04.007

[9]. Deng, T., Norris, S., & Sharma, R. N. (2021). Numerical investigation on the stability of tunnel smoke stratification under the effect of water spray and longitudinal ventilation. *Tunnelling and Underground Space Technology*, *112*, 103901. https://doi.org/10.1016/j.tust.2021.103901

[10]. Deng, T., Sharma, R. N., & Norris, S. (2022). Effects of the water spray system on the air-driving force required in longitudinally ventilated road tunnels. *Tunnelling and Underground Space Technology*, *130*, 104753. https://doi.org/10.1016/j.tust.2022.104753

[11]. Efat Ara, H. (2025). The Role of Calibration Engineering In Strengthening Reliability Of U.S. Advanced Manufacturing Systems Through Artificial Intelligence. *Review of Applied Science and Technology*, *4*(02), 820-851. https://doi.org/10.63125/0y0m8x22

[12]. Festag, S. (2016). False alarm ratio of fire detection and fire alarm systems in Germany – A meta analysis. *Fire Safety Journal*, *79*, 119–126. https://doi.org/10.1016/j.firesaf.2015.11.010

[13]. Frank, K., Gravestock, N., Spearpoint, M., & Fleischmann, C. (2013). A review of sprinkler system effectiveness studies. *Fire Science Reviews*, *2*, 6. https://doi.org/10.1186/2193-0414-2-6

[14]. Gaur, A., Singh, A., Kumar, A., Kumar, A., Kapoor, K., & Bhatia, T. (2020). Video flame and smoke based fire detection algorithms: A literature review. *Fire Technology*, *56*, 1943–1980. https://doi.org/10.1007/s10694-020-00986-y

[15]. Habibullah, S. M. (2025). Swarm Intelligence-Based Autonomous Logistics Framework With Edge AI For Industry 4.0 Manufacturing Ecosystems. *Review of Applied Science and Technology*, *4*(03), 01-34. https://doi.org/10.63125/p1q8yf46

[16]. Holden, R. J., & Karsh, B.-T. (2010). The Technology Acceptance Model: Its past and its future in health care. *Journal of Biomedical Informatics*, *43*(1), 159–172. https://doi.org/10.1016/j.jbi.2009.07.002

[17]. Hong, Y., Fu, C., & Merci, B. (2022). Numerical analysis of the performance of a PID control based real-time mechanical ventilation system to prevent smoke back-layering in tunnel fires. *Tunnelling and Underground Space Technology*, *128*, 104639. https://doi.org/10.1016/j.tust.2022.104639

[18]. Hozyfa, S., & Ashraful, I. (2025). Impact Of Data Privacy And Cybersecurity In Accounting Information Systems On Financial Transparency. *International Journal of Scientific Interdisciplinary Research*, *6*(1), 254–292. https://doi.org/10.63125/xs0xt970

[19]. Hozyfa, S., & Mst. Shahrin, S. (2024). The Influence Of Secure Data Systems On Fraud Detection In Business Intelligence Applications. *Journal of Sustainable Development and Policy*, *3*(04), 133-173. https://doi.org/10.63125/8ee0eq13

[20]. Hu, Y.-C., & Lu, X.-B. (2018). Real-time video fire/smoke detection by utilizing spatial-temporal ConvNet features. *Multimedia Tools and Applications*, *77*, 29273–29290. https://doi.org/10.1007/s11042-018-5978-5

[21]. Huang, L., Liu, G., Wang, Y., Yuan, H., & Chen, T. (2022). Fire detection in video surveillances using convolutional neural networks and wavelet transform. *Engineering Applications of Artificial Intelligence*, *115*, 104737. https://doi.org/10.1016/j.engappai.2022.104737

[22]. Jabed Hasan, T., & Mohammad Shah, P. (2024). Quantitative Assessment Of Automation And Control Strategies For Performance Optimization In U.S. Industrial Plants. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *4*(1), 169–205. https://doi.org/10.63125/eqfz8220

[23]. Jabed Hasan, T., & Zayadul, H. (2024). Adapting PLC/SCADA Systems To Mitigate Industrial IOT Cybersecurity Risks In Global Manufacturing. *American Journal of Interdisciplinary Studies*, *5*(04), 67-95. https://doi.org/10.63125/0v4cms60

[24]. Jafari, M. J., Pouyakian, M., Khanteymoori, A., & Hanifi, S. M. (2020). Reliability evaluation of fire alarm systems using dynamic Bayesian networks and fuzzy fault tree analysis. *Journal of Loss Prevention in the Process Industries*, *67*, 104229. https://doi.org/10.1016/j.jlp.2020.104229

[25]. Jahid, M. K. A. S. R. (2021). Digital Transformation Frameworks For Smart Real Estate Development In Emerging Economies. *Review of Applied Science and Technology*, *6*(1), 139–182. https://doi.org/10.63125/cd09ne09

[26]. Jiang, J., Chen, L., Jiang, S., Li, G.-Q., & Usmani, A. S. (2015). Fire safety assessment of super tall buildings: A case study on Shanghai Tower. *Case Studies in Fire Safety*, *4*, 28–38. https://doi.org/10.1016/j.csfs.2015.06.001

[27]. Jiang, L., Shi, J., Wang, C., & Pan, Z. (2022). Intelligent control of building fire protection system using digital twins and semantic web technologies. *Automation in Construction*, *147*, 104728. https://doi.org/10.1016/j.autcon.2022.104728

[28]. Khalil, N., Kamaruzzaman, S. N., Baharum, M. R., & Husin, H. N. (2016). The performance-risk indicators (PRI) in building performance rating tool for higher education buildings. *Journal of Facilities Management*, *14*(1), 6–22. https://doi.org/10.1108/jfm-03-2015-0009

[29]. King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management*, *43*(6), 740–755. https://doi.org/10.1016/j.im.2006.05.003

[30]. Ko, B.-C., Cheong, K.-H., & Nam, J.-Y. (2010). Early fire detection algorithm based on irregular patterns of flames and hierarchical Bayesian networks. *Fire Safety Journal*, *45*, 262–270. https://doi.org/10.1016/j.firesaf.2010.04.001

[31]. Lin, G., Zhang, Y., Xu, G., & Zhang, Q. (2019). Smoke detection on video sequences using 3D convolutional neural networks. *Fire Technology*, *55*, 1827–1847. https://doi.org/10.1007/s10694-019-00832-w

[32]. Lovreglio, R., & Kuligowski, E. (2022). A pre-evacuation study using data from evacuation drills and false alarm evacuations in a university library. *Fire Safety Journal*, *129*, 103595. https://doi.org/10.1016/j.firesaf.2022.103595

[33]. MacLeod, J., Tan, S., & Moinuddin, K. (2020). Reliability of fire (point) detection system in office buildings in Australia – A fault tree analysis. *Fire Safety Journal*, *115*, 103150. https://doi.org/10.1016/j.firesaf.2020.103150

[34]. Maltezos, E., Petousakis, K., Dadoukis, A., Karagiannidis, L., Ouzounoglou, E., Krommyda, M., Hadjipavlis, G., & Amditis, A. (2022). A smart building fire and gas leakage alert system with edge computing and NG112 emergency call capabilities. *Information*, *13*(4), 164. https://doi.org/10.3390/info13040164

[35]. Marangunić, N., & Granić, A. (2015). Technology acceptance model: A literature review from 1986 to 2013. *Universal Access in the Information Society*, *14*, 81–95. https://doi.org/10.1007/s10209-014-0348-1

[36]. Md Al Amin, K., & Md Mesbaul, H. (2023). Smart Hybrid Manufacturing: A Combination Of Additive, Subtractive, And Lean Techniques For Agile Production Systems. *Journal of Sustainable Development and Policy*, *2*(04), 174-217. https://doi.org/10.63125/7rb1zz78

[37]. Md Ariful, I., & Efat Ara, H. (2022). Advances And Limitations Of Fracture Mechanics–Based Fatigue Life Prediction Approaches For Structural Integrity Assessment: A Systematic Review. *American Journal of Interdisciplinary Studies*, *3*(03), 68-98. https://doi.org/10.63125/fg8ae957

[38]. Md Arman, H., & Md.Kamrul, K. (2022). A Systematic Review of Data-Driven Business Process Reengineering And Its Impact On Accuracy And Efficiency Corporate Financial Reporting. *International Journal of Business and Economics Insights*, *2*(4), 01–41. https://doi.org/10.63125/btx52a36

[39]. Md Asfaquar, R. (2025). Vehicle-To-Infrastructure (V2I) Communication And Traffic Incident Reduction: An Empirical Study Across U.S. Highway Networks. *Journal of Sustainable Development and Policy*, *4*(03), 38-81. https://doi.org/10.63125/c1wm0t92

[40]. Md Foysal, H. (2025). Integration Of Lean Six Sigma and Artificial Intelligence-Enabled Digital Twin Technologies For Smart Manufacturing Systems. *Review of Applied Science and Technology*, *4*(04), 01-35. https://doi.org/10.63125/1med8n85

[41]. Md Foysal, H., & Aditya, D. (2023). Smart Continuous Improvement With Artificial Intelligence, Big Data, And Lean Tools For Zero Defect Manufacturing Systems. *American Journal of Scholarly Research and Innovation*, *2*(01), 254–282. https://doi.org/10.63125/6cak0s21

[42]. Md Hamidur, R. (2023). Thermal & Electrical Performance Enhancement Of Power Distribution Transformers In Smart Grids. *American Journal of Scholarly Research and Innovation*, *2*(01), 283–313. https://doi.org/10.63125/n2p6y628

[43]. Md Harun-Or-Rashid, M., Mst. Shahrin, S., & Sai Praveen, K. (2023). Integration Of IOT And EDGE Computing For Low-Latency Data Analytics In Smart Cities And IOT Networks. *Journal of Sustainable Development and Policy*, *2*(03), 01-33. https://doi.org/10.63125/004h7m29

[44]. Md Majadul Islam, J., & Md Abdur, R. (2025). Enhancing Decision-Making in U.S. Enterprises With Artificial Intelligence-Driven Business Intelligence Models. *International Journal of Business and Economics Insights*, *5*(3), 100–133. https://doi.org/10.63125/8n54qm32

[45]. Md Mesbaul, H., & Md. Tahmid Farabe, S. (2022). Implementing Sustainable Supply Chain Practices In Global Apparel Retail: A Systematic Review Of Current Trends. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *2*(1), 332–363. https://doi.org/10.63125/nen7vd57

[46]. Md Mohaiminul, H. (2025). Federated Learning Models for Privacy-Preserving AI In Enterprise Decision Systems. *International Journal of Business and Economics Insights*, *5*(3), 238– 269. https://doi.org/10.63125/ry033286

[47]. Md Mominul, H. (2025). Systematic Review on The Impact Of AI-Enhanced Traffic Simulation On U.S. Urban Mobility And Safety. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 833–861. https://doi.org/10.63125/jj96yd66

[48]. Md Musfiqur, R., & Md.Kamrul, K. (2023). Mechanisms By Which AI-Enabled Crm Systems Influence Customer Retention And Overall Business Performance: A Systematic Literature Review Of Empirical Findings. *International Journal of Business and Economics Insights*, *3*(1), 31-67. https://doi.org/10.63125/qqe2bm11

[49]. Md Muzahidul, I. (2025). The Impact Of Data-Driven Web Frameworks On Performance And Scalability Of U.S. Enterprise Applications. *International Journal of Business and Economics Insights*, *5*(3), 523–558. https://doi.org/10.63125/f07n4p12

[50]. Md Muzahidul, I., & Aditya, D. (2024). Predictive Analytics And Data-Driven Algorithms For Improving Efficiency In Full-Stack Web Systems. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 226–260. https://doi.org/10.63125/q75tbj05

[51]. Md Muzahidul, I., & Md Mohaiminul, H. (2023). Explainable AI (XAI) Models For Cloud-Based Business Intelligence: Ensuring Compliance And Secure Decision-Making. *American Journal of Interdisciplinary Studies*, *4*(03), 208–249. https://doi.org/10.63125/5etfhh77

[52]. Md Nahid, H. (2022). Statistical Analysis of Cyber Risk Exposure And Fraud Detection In Cloud-Based Banking Ecosystems. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *2*(1), 289–331. https://doi.org/10.63125/9wf91068

[53]. Md Sarwar Hossain, S. (2025). Artificial Intelligence In Driven Digital Twin For Real-Time Traffic Signal Optimization And Transportation Planning. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 1316–1358. https://doi.org/10.63125/dthvcp78

[54]. Md Sarwar Hossain, S., & Md Milon, M. (2022). Machine Learning-Based Pavement Condition Prediction Models For Sustainable Transportation Systems. *American Journal of Interdisciplinary Studies*, *3*(01), 31–64. https://doi.org/10.63125/1jsmkg92

[55]. Md Wahid Zaman, R. (2025). The Role Of Data Science In Optimizing Project Efficiency And Innovation In U.S. Enterprises. *International Journal of Business and Economics Insights*, *5*(3), 586–600. https://doi.org/10.63125/jzjkqm27

[56]. Md. Abdur, R., & Zamal Haider, S. (2022). Assessment Of Data-Driven Vendor Performance Evaluation In Retail Supply Chains Analyzing Metrics, Scorecards, And Contract Management Tools. *Journal of Sustainable Development and Policy*, *1*(04), 71-116. https://doi.org/10.63125/2a641k35

[57]. Md. Akbar, H., & Sharmin, A. (2025). AI-Enabled Neurobiological Diagnostic Models For Early Detection Of PTSD And Trauma Disorders. *American Journal of Interdisciplinary Studies*, *6*(02), 01–39. https://doi.org/10.63125/64hftc92

[58]. Md. Al Amin, K., & Sai Praveen, K. (2023). The Role Of Industrial Engineering In Advancing Sustainable Manufacturing And Quality Compliance In Global Engineering Systems. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 31–61. https://doi.org/10.63125/8w1vk676

[59]. Md. Hasan, I. (2025). A Systematic Review on The Impact Of Global Merchandising Strategies On U.S. Supply Chain Resilience. *International Journal of Business and Economics Insights*, *5*(3), 134–169. https://doi.org/10.63125/24mymg13

[60]. Md. Hasan, I., & Ashraful, I. (2023). The Effect Of Production Planning Efficiency On Delivery Timelines In U.S. Apparel Imports. *Journal of Sustainable Development and Policy*, *2*(04), 35-73. https://doi.org/10.63125/sg472m51

[61]. Md. Hasan, I., & Rakibul, H. (2024). Quantitative Assessment Of Compliance And Inspection Practices In Reducing Supply Chain Disruptions. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 301–342. https://doi.org/10.63125/db63r616

[62]. Md. Jobayer Ibne, S. (2025). AI-Enhanced Business Intelligence Dashboards For Predictive Market Strategy In U.S. Enterprises. *International Journal of Business and Economics Insights*, *5*(3), 603–648. https://doi.org/10.63125/8cvgn369

[63]. Md. Jobayer Ibne, S., & Md. Kamrul, K. (2023). Automating NIST 800-53 Control Implementation: A Cross-Sector Review Of Enterprise Security Toolkits. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *3*(1), 160–195. https://doi.org/10.63125/prkw8r07

[64]. Md. Milon, M. (2025). A Systematic Review on The Impact Of NFPA-Compliant Fire Protection Systems On U.S. Infrastructure Resilience. *International Journal of Business and Economics Insights*, *5*(3), 324–352. https://doi.org/10.63125/ne3ey612

[65]. Md. Mominul, H. (2024). Quantitative Assessment Of Smart City IOT Integration For Reducing Urban Infrastructure Vulnerabilities. *Review of Applied Science and Technology*, *3*(04), 48-93. https://doi.org/10.63125/f2cj4507

[66]. Md. Mominul, H., & Syed Zaki, U. (2024). A Review On Sustainable Building Materials And Their Role In Enhancing U.S. Green Infrastructure Goals. *Journal of Sustainable Development and Policy*, *3*(04), 65-100. https://doi.org/10.63125/bfmmay79

[67]. Md. Tahmid Farabe, S. (2025). The Impact of Data-Driven Industrial Engineering Models On Efficiency And Risk Reduction In U.S. Apparel Supply Chains. *International Journal of Business and Economics Insights*, *5*(3), 353–388. https://doi.org/10.63125/y548hz02

[68]. Md.Akbar, H., & Farzana, A. (2021). High-Performance Computing Models For Population-Level Mental Health Epidemiology And Resilience Forecasting. *American Journal of Health and Medical Sciences*, *2*(02), 01–33. https://doi.org/10.63125/k9d5h638

[69]. Md.Kamrul, K. (2025). Bayesian Statistical Models For Predicting Type 2 Diabetes Prevalence In Urban Populations. *Review of Applied Science and Technology*, *4*(02), 370-406. https://doi.org/10.63125/db2e5054
[70]. Mohammad Mushfequr, R. (2025). The Role Of AI-Enabled Information Security Frameworks in Preventing Fraud In U.S. Healthcare Billing Systems. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 1160–1201. https://doi.org/10.63125/y068m490
[71]. Mohammad Mushfequr, R., & Ashraful, I. (2023). Automation And Risk Mitigation in Healthcare Claims: Policy And Compliance Implications. *Review of Applied Science and Technology*, *2*(04), 124–157. https://doi.org/10.63125/v73gyg14
[72]. Mohammad Mushfequr, R., & Sai Praveen, K. (2022). Quantitative Investigation Of Information Security Challenges In U.S. Healthcare Payment Ecosystems. *International Journal of Business and Economics Insights*, *2*(4), 42–73. https://doi.org/10.63125/gcg0fs06
[73]. Mortuza, M. M. G., & Rauf, M. A. (2022). Industry 4.0: An Empirical Analysis of Sustainable Business Performance Model Of Bangladeshi Electronic Organisations. *International Journal of Economy and Innovation*. https://gospodarkainnowacje.pl/index.php/issue_view_32/article/view/826
[74]. Mst. Shahrin, S. (2025). Predictive Neural Network Models for Cyberattack Pattern Recognition And Critical Infrastructure Vulnerability Assessment. *Review of Applied Science and Technology*, *4*(02), 777-819. https://doi.org/https://rast-journal.org/index.php/RAST/article/view/48
[75]. Muhammad, K., Ahmad, J., Mehmood, I., Rho, S., & Baik, S. W. (2018a). Convolutional neural networks based fire detection in surveillance videos. *IEEE Access*, *6*, 18174–18183. https://doi.org/10.1109/access.2018.2812835
[76]. Muhammad, K., Ahmad, J., Mehmood, I., Rho, S., & Baik, S. W. (2018b). Early fire detection using convolutional neural networks during surveillance for effective disaster management. *Neurocomputing*, *288*, 30–42. https://doi.org/10.1016/j.neucom.2017.04.083
[77]. Noreen, U., Ahmed, S., Qadir, J., & et al. (2019). An intelligent fire warning application using IoT and an adaptive neural network. *Sensors*, *19*(14), 3150. https://doi.org/10.3390/s19143150
[78]. Ouedraogo, C. A., Maré, D., Martineau, M., & Khoukhi, L. (2018). Deployment of IoT edge and fog computing technologies to develop smart buildings. *Sustainability*, *10*(11), 3832. https://doi.org/10.3390/su10113832
[79]. Pankaz Roy, S., & Md. Kamrul, K. (2023). HACCP and ISO Frameworks For Enhancing Biosecurity In Global Food Distribution Chains. *American Journal of Scholarly Research and Innovation*, *2*(01), 314–356. https://doi.org/10.63125/9pbp4h37
[80]. Pankaz Roy, S., & Sai Praveen, K. (2024). Systematic Review of Stress And Burnout Interventions Among U.S. Healthcare Professionals Using Advanced Computing Approaches. *Journal of Sustainable Development and Policy*, *3*(04), 101-132. https://doi.org/10.63125/9mx2fc43
[81]. Rakibul, H. (2025). The Role of Business Analytics In ESG-Oriented Brand Communication: A Systematic Review Of Data-Driven Strategies. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 1096– 1127. https://doi.org/10.63125/4mchj778
[82]. Rakibul, H., & Samia, A. (2022). Information System-Based Decision Support Tools: A Systematic Review Of Strategic Applications In Service-Oriented Enterprises. *Review of Applied Science and Technology*, *1*(04), 26-65. https://doi.org/10.63125/w3cevz78
[83]. Reza, M., Vorobyova, K., & Rauf, M. (2021). The effect of total rewards system on the performance of employees with a moderating effect of psychological empowerment and the mediation of motivation in the leather industry of Bangladesh. *Engineering Letters*, *29*, 1-29.
[84]. Rony, M. A., & Ashraful, I. (2022). Big Data And Engineering Analytics Pipelines For Smart Manufacturing: Enhancing Efficiency, Quality, And Predictive Maintenance. *American Journal of Scholarly Research and Innovation*, *1*(02), 59–85. https://doi.org/10.63125/rze0my79
[85]. Rony, M. A., & Hozyfa, S. (2024). Cloud-Integrated Digital Twin Architectures For Real-Time Monitoring, Risk Assessment, And Safety Optimization In U.S. Energy Infrastructure. *American Journal of Interdisciplinary Studies*, *5*(04), 96-133. https://doi.org/10.63125/y9m5pz24
[86]. Ruiz-Zafra, A., Benghazi, K., & Noguera, M. (2022). IFC+: Towards the integration of IoT into early stages of building design. *Automation in Construction*, 104129. https://doi.org/10.1016/j.autcon.2022.104129
[87]. Saba, A. (2025). Artificial Intelligence Based Models For Secure Data Analytics And Privacy-Preserving Data Sharing In U.S. Healthcare And Hospital Networks. *International Journal of Business and Economics Insights*, *5*(3), 65–99. https://doi.org/10.63125/wv0bqx68
[88]. Saba, A., & Md. Sakib Hasan, H. (2024). Machine Learning And Secure Data Pipelines For Enhancing Patient Safety In Electronic Health Record (EHR) Among U.S. Healthcare Providers. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *4*(1), 124–168. https://doi.org/10.63125/qm4he747
[89]. Saba, A., Shaikat, B., & Tonoy Kanti, C. (2023). Integration Of Artificial Intelligence And Advanced Computing To Develop Resilient Cyber Defense Systems. *Journal of Sustainable Development and Policy*, *2*(04), 74-107. https://doi.org/10.63125/rxyc6y88
[90]. Saba, A., & Tonoy Kanti, C. (2023). Explainable Artificial Intelligence (XAI) Approaches For Cyber Risk Assessment In Financial Services. *American Journal of Interdisciplinary Studies*, *4*(03), 96-135. https://doi.org/10.63125/3gjcb322
[91]. Sai Praveen, K. (2025). AI-Driven Data Science Models for Real-Time Transcription And Productivity Enhancement In U.S. Remote Work Environments. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 801–832. https://doi.org/10.63125/gzyw2311
[92]. Saikat, S. (2021). Real-Time Fault Detection in Industrial Assets Using Advanced Vibration Dynamics And Stress Analysis Modeling. *American Journal of Interdisciplinary Studies*, *2*(04), 39–68. https://doi.org/10.63125/0h163429

[93]. Saikat, S. (2022). CFD-Based Investigation of Heat Transfer Efficiency In Renewable Energy Systems. *International Journal of Scientific Interdisciplinary Research*, *1*(01), 129–162. https://doi.org/10.63125/ttw40456

[94]. Saikat, S. (2025). AI-Enabled Digital Twin Framework for Predictive Maintenance And Energy Optimization In Industrial Systems. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 1359–1389. https://doi.org/10.63125/8v1nwj69

[95]. Saponara, S., Elhanashi, A., & Zheng, A. (2020). Deep learning-based video fire detection for smart surveillance. *Journal of Real-Time Image Processing*, *17*, 451–464. https://doi.org/10.1007/s11554-020-01044-0

[96]. Schepers, J., & Wetzels, M. (2007). A meta-analysis of the technology acceptance model: Investigating subjective norm and moderation effects. *Information & Management*, *44*(1), 90–103. https://doi.org/10.1016/j.im.2006.10.007

[97]. Shaikat, B. (2025). Artificial Intelligence–Enhanced Cybersecurity Frameworks for Real-Time Threat Detection In Cloud And Enterprise. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 737–770. https://doi.org/10.63125/yq1gp452

[98]. Shaikat, B., & Md. Wahid Zaman, R. (2024). Quantum-Resistant Cryptographic Protocols Integrated With AI For Securing Cloud And IOT Environments. *International Journal of Business and Economics Insights*, *4*(4), 60–90. https://doi.org/10.63125/dryw3b96

[99]. Shaikh, S. (2025). AI-Orchestrated Cyber-Physical Systems For Sustainable Industry 5.0 Manufacturing And Supply Chain Resilience. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 1278–1315. https://doi.org/10.63125/jwm2e278

[100]. Shaikh, S., & Aditya, D. (2021). Federated Learning-Driven Predictive Quality Analytics and Supply Chain Optimization In Distributed Manufacturing Networks. *Review of Applied Science and Technology*, *6*(1), 74-107. https://doi.org/10.63125/k18cbz55

[101]. Shaikh, S., & Md. Tahmid Farabe, S. (2023). Digital Twin-Driven Process Modeling For Energy Efficiency And Lifecycle Optimization In Industrial Facilities. *American Journal of Interdisciplinary Studies*, *4*(03), 65–95. https://doi.org/10.63125/e4q64869

[102]. Shi, J., Ren, A., Chen, C., & Guo, W. (2019). Research on IFC- and FDS-based information sharing for building fire safety analysis. *Advances in Civil Engineering*, *2019*, 3604369. https://doi.org/10.1155/2019/3604369

[103]. Song, W. S., & Hong, S. H. (2006). A reference model of fire detection and monitoring system using BACnet. *Building and Environment*, *42*(2), 1000–1010. https://doi.org/10.1016/j.buildenv.2005.10.028

[104]. Spearpoint, M., Lovreglio, R., & Gwynne, S. (2021). The response of sleeping adults to smoke alarm signals in the evacuation decision model. *Fire Safety Journal*, *126*, 103379. https://doi.org/10.1016/j.firesaf.2021.103379

[105]. Sudipto, R., & Md. Hasan, I. (2024). Data-Driven Supply Chain Resilience Modeling Through Stochastic Simulation And Sustainable Resource Allocation Analytics. *American Journal of Advanced Technology and Engineering Solutions*, *4*(02), 01-32. https://doi.org/10.63125/p0ptag78

[106]. Sun, Y., & Turkan, Y. (2020). A BIM-based simulation framework for fire safety management and investigation of the factors affecting evacuation performance. *Advanced Engineering Informatics*, *44*, 101093. https://doi.org/10.1016/j.aei.2020.101093

[107]. Tang, S., Shelden, D. R., Eastman, C. M., Pishdad-Bozorgi, P., & Gao, X. (2019). A review of building information modeling (BIM) and the internet of things (IoT) devices integration: Present status and future trends. *Automation in Construction*, *101*, 127–139. https://doi.org/10.1016/j.autcon.2019.01.020

[108]. Tonoy Kanti, C. (2025). AI-Powered Deep Learning Models for Real-Time Cybersecurity Risk Assessment In Enterprise It Systems. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 675–704. https://doi.org/10.63125/137k6y79

[109]. Tonoy Kanti, C., & Saba, A. (2024). High-Performance Computing Architectures To Strengthen Cloud Infrastructure Security. *American Journal of Interdisciplinary Studies*, *5*(03), 01–42. https://doi.org/10.63125/9hr8qk06

[110]. Tonoy Kanti, C., & Sai Praveen, K. (2024). Federated Learning Models for Privacy-Preserving Data Sharing And Secure Analytics In Healthcare Industry. *International Journal of Business and Economics Insights*, *4*(4), 91-133. https://doi.org/10.63125/c2dzn006

[111]. Tonoy Kanti, C., & Shaikat, B. (2021). Blockchain-Enabled Security Protocols Combined With AI For Securing Next-Generation Internet Of Things (IOT) Networks. *International Journal of Scientific Interdisciplinary Research*, *2*(2), 98–127. https://doi.org/10.63125/pcdqzw41

[112]. Töreyin, B. U., Dedeoğlu, Y., Güdükbay, U., & Çetin, A. E. (2006). Computer vision based method for real-time fire and flame detection. *Pattern Recognition Letters*, *27*(1), 49–58. https://doi.org/10.1016/j.patrec.2005.06.015

[113]. Truong, X. T., & Kim, J.-M. (2011). An effective four-stage smoke-detection algorithm using video images for early fire-alarm systems. *Fire Safety Journal*, *46*(5), 276–282. https://doi.org/10.1016/j.firesaf.2011.03.003

[114]. Venkatesh, V., & Bala, H. (2008). Technology Acceptance Model 3 and a research agenda on interventions. *Decision Sciences*, *39*(2), 273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

[115]. Waladur, R., & Jabed Hasan, T. (2025). MODBUS/DNP3 Over TCP/IP Implementation On TMDSCNCD28388D and ARDUINO With SIMULINK HMI For IOT-Based Cybersecure Electrical Systems. *International Journal of Business and Economics Insights*, *5*(3), 494–522. https://doi.org/10.63125/8e9cm978

[116]. Węgrzyński, W., Krajewski, G., Tofiło, P., Jahn, W., Król, A., & Król, M. (2020). 3D mapping of the sprinkler activation time. *Energies*, *13*(6), 1450. https://doi.org/10.3390/en13061450

[117]. Wong, K. H.-L., & Xie, D.-Y. (2014). Fire safety management strategy of complex developments. *Procedia Engineering*, *71*, 410–420. https://doi.org/10.1016/j.proeng.2014.04.059

[118]. Xavier, J., & Nanayakkara, T. (2022). Development of an early fire detection technique using a passive infrared sensor and deep neural networks. *Fire Technology*, *58*, 3529–3552. https://doi.org/10.1007/s10694-022-01319-x

[119]. Xie, H., Lundteigen, M. A., & Rausand, M. (2009). Risk of human fatality in building fires: A decision tool using Bayesian networks. *Fire Safety Journal*, *44*, 704–710. https://doi.org/10.1016/j.firesaf.2009.01.006

[120]. Xin, Y., Dotson, J., Lock, A., Grosshandler, W., & Walton, W. (2017a). SMART sprinkler protection for highly challenging fires—Part 1: System design and function evaluation. *Fire Technology*, *53*, 263–289. https://doi.org/10.1007/s10694-017-0662-2

[121]. Xin, Y., Dotson, J., Lock, A., Grosshandler, W., & Walton, W. (2017b). SMART sprinkler protection for highly challenging fires—Part 2: Fire suppression performance. *Fire Technology*, *53*, 291–312. https://doi.org/10.1007/s10694-017-0659-x

[122]. Ye, W., Zhao, J., Wang, S., Wang, Y., & Zhang, S. (2015). Dynamic texture based smoke detection using Surfacelet transform and HMT model. *Fire Safety Journal*, *73*, 91–101. https://doi.org/10.1016/j.firesaf.2015.03.001

[123]. Yuan, F. (2008). A fast accumulative motion orientation model based on integral image for video smoke detection. *Pattern Recognition Letters*, *29*(7), 925–932. https://doi.org/10.1016/j.patrec.2008.01.013

[124]. Yuan, F. (2011). Video-based smoke detection with histogram sequence of LBP and LBPV pyramids. *Fire Safety Journal*, *46*, 132–139. https://doi.org/10.1016/j.firesaf.2011.01.001

[125]. Zamal Haider, S. (2025). Securing ERP Systems: The Role Of Information Security Analysts In U.S. Textile And Manufacturing Enterprises. *International Journal of Business and Economics Insights*, *5*(3), 459–493. https://doi.org/10.63125/y8evt228

[126]. Zamal Haider, S., & Hozyfa, S. (2023). A Quantitative Study On IT-Enabled ERP Systems And Their Role In Operational Efficiency. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 62–99. https://doi.org/10.63125/nbpyce10

[127]. Zamal Haider, S., & Sai Praveen, K. (2024). Cloud-Native Data Pipelines For Scalable Audio Analytics And Secure Enterprise Applications. *American Journal of Scholarly Research and Innovation*, *3*(01), 52-83. https://doi.org/10.63125/m4f2aw73

[128]. Zervas, E., Mpimpoudis, A., Anagnostopoulos, C.-N., Sekkas, O., & Hadjiefthymiades, S. (2011). Multisensor data fusion for fire detection. *Information Fusion*, *12*(3), 150–159. https://doi.org/10.1016/j.inffus.2009.12.006

[129]. Zhang, Q., Lin, G., Zhang, Y., Xu, G., & Wang, J. (2018). Wildland forest fire smoke detection based on Faster R-CNN using synthetic smoke images. *Procedia Engineering*, *211*, 441–446. https://doi.org/10.1016/j.proeng.2017.12.034

[130]. Zobayer, E. (2021a). Data Driven Predictive Maintenance In Petroleum And Power Systems Using Random Forest Regression Model For Reliability Engineering Framework. *Review of Applied Science and Technology*, *6*(1), 108-138. https://doi.org/10.63125/5bjx6963

[131]. Zobayer, E. (2021b). Machine Learning Approaches For Optimization Of Lubricant Performance And Reliability In Complex Mechanical And Manufacturing Systems. *American Journal of Scholarly Research and Innovation*, *1*(01), 61–92. https://doi.org/10.63125/5zvkgg52

[132]. Zobayer, E. (2023). IOT Integration In Intelligent Lubrication Systems For Predictive Maintenance And Performance Optimization In Advanced Manufacturing Industries. *Journal of Sustainable Development and Policy*, *2*(04), 140-173. https://doi.org/10.63125/zybrmx69

[133]. Zobayer, E., & Sabuj Kumar, S. (2024). Enhancing HFO Separator Efficiency: A Data-Driven Approach To Petroleum Systems Optimization. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 261–300. https://doi.org/10.63125/2tzaap28

[134]. Zulqarnain, F. N. U., & Zayadul, H. (2024). Artificial Intelligence Applications For Predicting Renewable-Energy Demand Under Climate Variability. *American Journal of Scholarly Research and Innovation*, *3*(01), 84–116. https://doi.org/10.63125/sg0j6930