American Journal of Advanced Technology and Engineering Solutions
Volume 01 Issue 01 (2025)
Page No: 174-200
DOI:10.63125/xcxwpv34

Article

AI-BASED EMERGENCY RESPONSE SYSTEMS: A SYSTEMATIC LITERATURE REVIEW ON SMART INFRASTRUCTURE SAFETY

Ammar Bajwa[1]

[1]*Master of Engineering (M.E.), Electrical and Electronics Engineering, Lamar University, USA*
Email: ammar.bajwa1@gmail.com

ABSTRACT

Artificial intelligence (AI)-based emergency response systems have emerged as critical enablers of smart infrastructure safety, offering enhanced real-time decision-making, risk assessment, and disaster mitigation strategies across various domains. This systematic literature review, encompassing 424 eligible studies, investigates the integration of machine learning (ML), deep learning (DL), computer vision, IoT-enabled predictive analytics, and AI-powered robotics in optimizing emergency response mechanisms. The study comprehensively examines AI applications in disaster management, real-time incident detection, healthcare emergency response, industrial hazard prevention, cybersecurity frameworks, and intelligent traffic control, providing a detailed assessment of technological advancements and challenges in AI adoption. The findings reveal that AI has significantly improved predictive accuracy, automated hazard detection, and emergency resource optimization, leading to faster response times, minimized human error, and enhanced situational awareness in crisis management. AI-driven predictive analytics models have enabled early warning systems for earthquakes, floods, and wildfires, facilitating proactive disaster preparedness and risk mitigation. In real-time emergency response, AI-powered computer vision and sensor-based surveillance technologies have improved incident detection, reducing intervention delays and ensuring more efficient allocation of emergency resources. In the healthcare sector, AI-enhanced diagnostic tools, triage automation, and geospatial analytics for ambulance dispatch have streamlined medical crisis management, improving survival rates and reducing treatment delays. Additionally, AI-integrated industrial safety frameworks, robotic automation, and cybersecurity intelligence systems have strengthened workplace hazard prevention, cyber threat detection, and emergency communication resilience, ensuring safer and more secure operational environments. Despite these advancements, several challenges related to interoperability, regulatory constraints, cybersecurity vulnerabilities, algorithmic biases, and ethical concerns persist, hindering large-scale AI adoption in emergency response systems. This review provides a comprehensive synthesis of AI's transformative role in modern emergency management, offering insights into technological developments, limitations, and policy considerations necessary to enhance AI-driven crisis response strategies and ensure more effective, scalable, and resilient emergency safety infrastructures worldwide.

KEYWORDS

AI-Based Emergency Response; Smart Infrastructure Safety; Disaster Management; IoT and Predictive Analytics; Real-Time Incident Detection

Citation:
Bajwa, A. (2025). AI-based emergency response systems: A systematic literature review on smart infrastructure safety. *American Journal of Advanced Technology and Engineering Solutions, 1*(1), 20-40. https://doi.org/10.63125/xcxwpv34

Received:
November 11, 2024

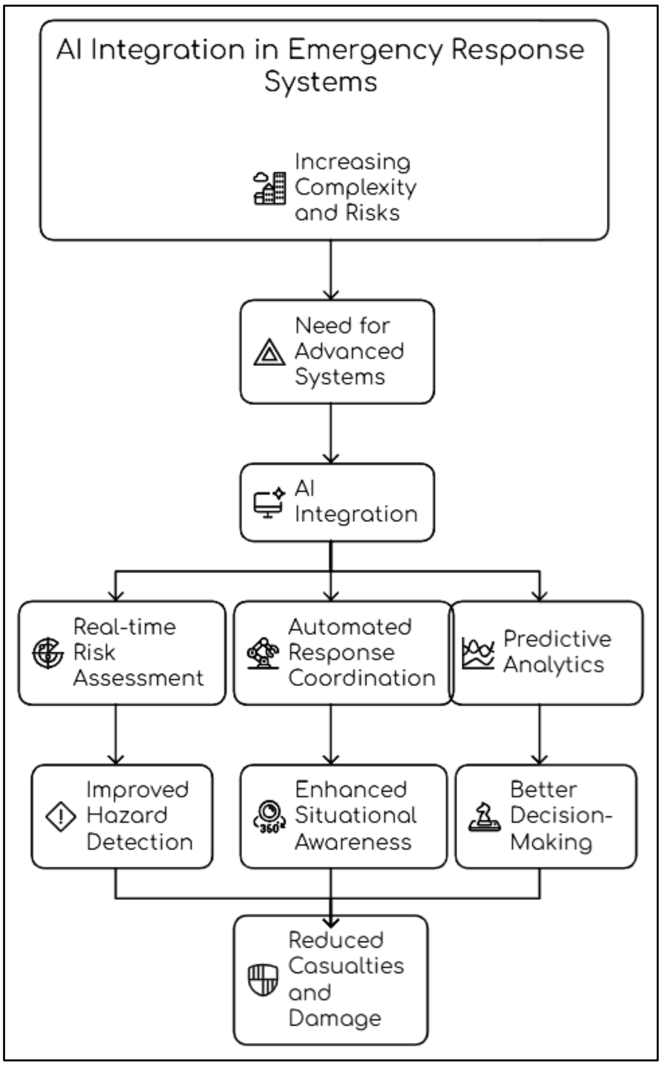
Revised:
January 19, 2025

Accepted:
February 25, 2025

Published:
March 05, 2025

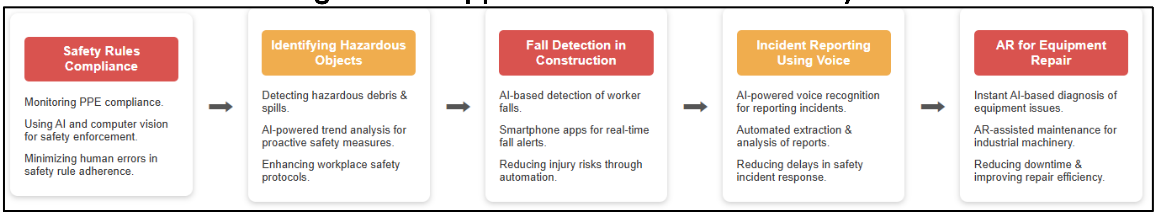
INTRODUCTION

The increasing complexity of modern urban infrastructure, coupled with the rising frequency of natural and man-made disasters, has necessitated the development of advanced emergency response systems that enhance safety and resilience (Caprotti & Cowley, 2019). Traditional emergency response mechanisms, which rely heavily on manual decision-making and human intervention, are often hindered by delays, inefficiencies, and a lack of real-time situational awareness (Evgrafova et al., 2022). The integration of artificial intelligence (AI) in emergency management has revolutionized the field by enabling real-time risk assessment, automated response coordination, and predictive analytics (Ghaffarian et al., 2018). AI-driven technologies, including machine learning (ML), deep learning (DL), computer vision, and the Internet of Things (IoT), have demonstrated their potential to optimize disaster preparedness and improve emergency response effectiveness (Kong & Woods, 2018). These advancements have led to automated hazard detection, enhanced situational awareness, and improved decision-making, significantly reducing casualties and infrastructure damage during critical incidents (Leszczynski, 2016). The growing body of research on AI-based emergency response systems highlights their ability to process vast amounts of data, detect anomalies, and provide actionable insights that human responders might overlook in high-pressure situations (Li et al., 2023). The deployment of AI-powered emergency management solutions spans a variety of disaster scenarios, including natural catastrophes such as earthquakes, floods, and wildfires, as well as industrial hazards, medical emergencies, and cybersecurity threats (Pollio, 2016). AI-driven early warning systems have significantly improved disaster preparedness by leveraging historical data, satellite imagery, and real-time sensor inputs to forecast potential risks with high accuracy (Ruiying et al., 2019). For instance, earthquake prediction models based on deep learning algorithms have successfully analyzed seismic activity patterns to provide early warnings, minimizing the impact on human life and infrastructure (Smigiel, 2018). Similarly, AI-integrated flood monitoring systems utilize remote sensing data and hydrological models to predict and mitigate flood risks in urban areas (Yao & Wang, 2020). Wildfire management has also benefited from AI-powered computer vision models and geospatial analytics, which enhance fire detection capabilities by analyzing satellite and drone imagery in real time (Kong & Woods, 2018). These predictive and real-time monitoring tools have drastically improved the ability of emergency agencies to respond proactively, reducing the loss of life and economic damage associated with large-scale disasters (Evgrafova et al., 2022).



AI-based emergency response systems have also played a transformative role in transportation safety and traffic incident management. The rapid urbanization of smart cities has led to increased reliance on AI-powered traffic monitoring systems, which leverage computer vision, deep learning, and IoT-enabled sensors to enhance road safety (Beg et al., 2020). AI-driven video analytics solutions can detect traffic congestion, vehicular accidents, and hazardous conditions in real time, allowing authorities to take immediate action and prevent further complications (Chen et al., 2017). Moreover, AI-powered intelligent traffic control systems utilize reinforcement learning algorithms to optimize traffic signal timings, reducing emergency response delays and improving road network efficiency (Getuli et al., 2021). In addition, autonomous emergency vehicles equipped with AI-enhanced navigation systems can dynamically adapt their routes based on real-time congestion data and predictive analytics, ensuring faster response times for ambulances, fire trucks, and law enforcement agencies (Green et al., 2020). These AI-integrated traffic solutions have enhanced urban mobility and significantly reduced fatal accident rates, demonstrating their potential for wide-scale implementation in smart infrastructure safety frameworks (Xiao et al., 2017). Moreover, the integration of AI in healthcare emergency response has led to significant advancements in early disease detection, emergency triage optimization, and automated patient monitoring (Green et al., 2020). AI-powered predictive analytics models have been employed to detect early signs of cardiac arrest, strokes, and respiratory failure, enabling rapid intervention and timely medical response (Getuli et al., 2021). In emergency departments, AI-based triage systems leveraging natural language processing (NLP) and deep learning assist healthcare professionals in prioritizing patients based on symptom severity, thereby reducing wait times and improving critical care outcomes (Chen et al., 2017). Additionally, AI-integrated wearable devices and IoT-based patient monitoring systems continuously track vital signs, automatically alerting medical personnel in case of anomalies (Beg et al., 2020). The role of AI in ambulance dispatch and route optimization has also been significant, as AI-driven geospatial analytics tools determine the fastest routes to hospitals based on real-time traffic conditions and historical travel patterns (Chen et al., 2017). The ability of AI-powered healthcare systems to streamline emergency response operations, enhance decision-making, and reduce medical errors highlights their growing importance in modern healthcare infrastructure (Getuli et al., 2021).

Figure 1: AI Applications for Industrial Safety



AI-based industrial safety and hazardous event prevention systems have also demonstrated substantial improvements in real-time risk detection and anomaly recognition (Almatared et al., 2023). AI-powered sensor-based monitoring systems continuously analyze environmental and operational data to detect toxic gas leaks, fire hazards, and equipment malfunctions in manufacturing plants, refineries, and chemical facilities (Alsarhan et al., 2018). These automated early warning systems, combined with IoT and deep learning techniques, allow companies to implement proactive predictive maintenance strategies, reducing workplace accidents and operational downtime ((Getuli et al., 2021). Furthermore, AI-driven robotics and autonomous drones are increasingly utilized in hazardous environments such as nuclear power plants, offshore oil rigs, and mining operations, where human intervention poses significant risks (Jiang et al., 2020). These AI-powered inspection tools enhance safety by enabling remote monitoring and real-time decision support, ensuring the protection of personnel and critical infrastructure (Fang et al., 2024). Moreover, cybersecurity has also become a critical component of AI-based emergency response frameworks, particularly in the protection of critical infrastructure and smart city networks (Getuli et al., 2021). AI-powered intrusion detection systems (IDS) employ deep learning and behavioral analytics to identify and neutralize cyber threats in real time, securing communication networks, financial systems, and industrial control mechanisms (Gura et al., 2020). The adoption of AI-driven blockchain security protocols has further enhanced emergency response systems by ensuring secure data transmission and authentication, mitigating the risks of cyberattacks and data breaches (Huang et al., 2022). Additionally, AI-enabled automated threat detection models are increasingly integrated into cloud-based emergency management platforms, providing enhanced security against ransomware, denial-of-service (DDoS) attacks, and network vulnerabilities (Khan et al., 2021). These AI-powered cybersecurity response mechanisms have strengthened the resilience of critical infrastructure, highlighting the essential role of AI in modern emergency preparedness and disaster mitigation strategies (Gura et al., 2020). AI-based emergency response systems have emerged as transformative tools in disaster management, healthcare, transportation, industrial safety, and cybersecurity, improving response efficiency, decision-making, and hazard prevention strategies (Alsarhan et al., 2018). The synergy between machine learning, IoT, and robotics has enabled automated risk detection, real-time monitoring, and proactive interventions, reinforcing the importance of AI-driven technologies in smart infrastructure safety (Fang et al., 2024). AI-driven response mechanisms continue to evolve and improve, demonstrating their capacity to optimize emergency preparedness, minimize human error, and enhance crisis management protocols in diverse application areas (Bieder, 2018).The primary objective of this systematic literature review is to examine the role of AI-based emergency response systems in enhancing smart infrastructure safety by synthesizing existing research on their applications, benefits, and challenges. Specifically, this study aims to (1) analyze the integration of machine learning, deep learning, IoT, and computer vision in emergency response mechanisms across various domains, including disaster management, transportation safety, healthcare emergencies, industrial hazard prevention, and cybersecurity; (2) evaluate the effectiveness of AI-driven risk prediction models, real-time monitoring systems, and automated decision-making frameworks in improving emergency response efficiency; and (3) identify key barriers to AI adoption, such as data security concerns, algorithmic biases, interoperability issues, and ethical considerations.

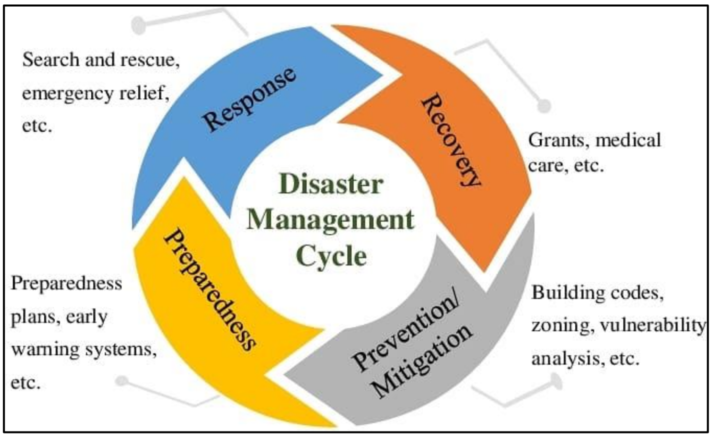
LITERATURE REVIEW

The integration of artificial intelligence (AI)-based emergency response systems in smart infrastructure safety has gained significant attention due to their ability to enhance real-time risk detection, response coordination, and disaster mitigation. AI-driven technologies such as machine learning, deep learning, computer vision, and IoT-enabled predictive analytics have revolutionized emergency preparedness and response by automating hazard detection, optimizing resource allocation, and improving situational awareness (Ćosić et al., 2024). Several studies have examined AI applications in various emergency response domains, including natural disaster management, traffic incident detection, healthcare emergency response, industrial hazard prevention, and cybersecurity (Jiang et al., 2020). However, challenges such as data security vulnerabilities, algorithmic biases, interoperability issues, and regulatory constraints have also been identified as barriers to large-scale AI adoption in emergency management (Khan et al., 2021). This literature review systematically examines existing research on AI-powered emergency response systems, focusing on their applications, technological innovations, and limitations. The section is structured into seven key thematic areas, each addressing a specific component of AI-based emergency management.

AI-Powered Disaster Prediction: Earthquake, Flood, and Wildfire Forecasting

The application of machine learning (ML) and deep learning (DL) in disaster prediction has significantly improved early warning systems by providing real-time data-driven insights and accurate forecasts. In earthquake prediction, AI models analyze seismic activity, historical earthquake patterns, and ground deformation data to predict potential tremors with higher precision than traditional statistical methods (Al-Turjman, 2019). Advanced ML techniques, including support vector machines (SVM), artificial neural networks (ANN), and convolutional neural networks (CNN), have been utilized to detect seismic anomalies and assess the likelihood of earthquakes in high-risk zones (AlHinai, 2020). Deep learning-based long short-term memory (LSTM) networks have further enhanced earthquake forecasting by identifying temporal dependencies in seismic sequences, enabling more reliable predictions (Bosher et al., 2007). AI-powered geospatial analytics and satellite imagery processing have also played a crucial role in earthquake impact assessment, helping authorities preemptively allocate resources and improve disaster preparedness strategies (Choi et al., 2020). These advancements underscore the increasing reliability of AI-driven models in reducing earthquake-related casualties and infrastructure damage through more precise predictions and early warnings (Fernando, 2020).

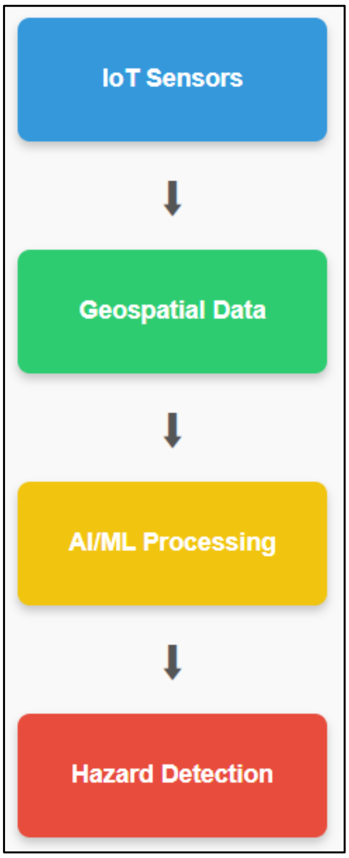
Figure 2: Disaster Management Cycle



AI applications in flood prediction have demonstrated their effectiveness in mitigating risks associated with urban flooding, river overflows, and coastal storm surges. Traditional hydrological models often struggle with the complexities of flood forecasting due to changing climate patterns and urbanization; however, machine learning models, such as random forests, gradient boosting machines (GBM), and deep neural networks (DNN), have significantly improved predictive accuracy by integrating real-time precipitation, soil moisture, and topographical data (Ghaffarian et al., 2018). Deep learning techniques, particularly recurrent neural networks (RNNs) and LSTMs, have been used to model the temporal evolution of hydrological events, providing better short-term and long-term flood forecasts (Dick et al., 2019). Additionally, AI-driven remote sensing techniques analyze synthetic aperture radar (SAR) and multispectral satellite imagery to detect flooding patterns and assess flood-prone areas (S. Khan et al., 2022). The use of AI-enhanced geographic information systems (GIS) has also facilitated flood mapping, allowing authorities to design adaptive drainage infrastructure and flood mitigation measures (Sun et al., 2013). These innovations highlight AI's growing role in improving flood early warning systems and minimizing disaster-related losses (Dick et al., 2019). In wildfire prediction and management, AI has been leveraged to identify fire-prone regions, assess fire spread dynamics, and optimize emergency response strategies. Traditional fire models rely on static datasets and predefined assumptions, often leading to delayed and inaccurate predictions. In contrast, ML and DL models process climate variables, vegetation dryness, wind speed, and topographical data to assess real-time wildfire risks (S. Khan et al., 2022). Deep learning techniques, such as CNN-based image classification models, have proven effective in analyzing satellite and drone imagery to detect fire outbreaks and assess burn severity (Joshi et al., 2016). AI-driven reinforcement learning models have also been utilized to simulate wildfire spread patterns and evaluate different firefighting strategies for improved resource allocation (Liu et al., 2017). Moreover, AI-integrated IoT-based environmental monitoring systems, equipped with smart sensors and edge computing, continuously analyze atmospheric conditions to provide real-time alerts on potential wildfire threats (Murphy, 2014). These technological advancements have enhanced wildfire prevention, detection, and containment, reducing the scale and intensity of fire disasters (Park et al., 2023). The effectiveness of machine learning and deep learning in disaster prediction has been widely recognized across earthquake, flood, and wildfire forecasting, demonstrating substantial improvements in accuracy, real-time monitoring, and risk mitigation. AI-driven early warning systems enhance disaster preparedness, optimize emergency response efforts, and support decision-making processes by analyzing complex datasets and detecting anomalies that traditional methods often miss (Garza-Reyes, 2015). However, challenges remain, particularly in ensuring data reliability, model generalizability, and computational efficiency across diverse geographic regions and environmental conditions (Qiang et al., 2021). The integration of multi-source data, high-performance computing, and AI-augmented geospatial analysis continues to strengthen disaster prediction frameworks, helping policymakers and emergency management agencies improve resilience against natural hazards (Sun et al., 2013).

Geospatial analytics and IoT-based sensor networks for hazard detection

The integration of geospatial analytics and Internet of Things (IoT)-based sensor networks has transformed hazard detection by providing real-time environmental monitoring, risk assessment, and disaster preparedness across multiple domains (Park et al., 2023). Geospatial analytics, which involves the analysis of spatial and temporal data from satellite imagery, remote sensing, and geographic information systems (GIS), has been widely employed for hazard detection and disaster response (Qiang et al., 2021). IoT-based sensor networks, on the other hand, utilize distributed smart sensors to continuously monitor environmental parameters such as temperature, humidity, seismic activity, air quality, and water levels, offering real-time alerts for potential disasters (Liu et al., 2017). Studies have demonstrated that machine learning-integrated geospatial analytics enhances the predictive capabilities of hazard detection systems, particularly in identifying patterns of natural disasters such as earthquakes, floods, wildfires, and landslides (Okrepilov et al., 2022). The use of high-resolution remote sensing data and AI-driven GIS applications has further facilitated the mapping of hazard-prone areas, enabling authorities to make data-driven decisions for risk mitigation (Qiang et al., 2021). In earthquake detection and early warning systems, IoT-based seismic sensor networks have been instrumental in analyzing ground vibrations and tectonic activity, allowing real-time assessment of seismic hazards (Song et al., 2017). These networks integrate edge computing and cloud-based AI analytics to process large volumes of seismic data, reducing the time required for earthquake intensity classification and epicenter localization (Qiang et al., 2021). Geospatial analytics-based fault line mapping has further contributed to seismic risk assessment by analyzing historical earthquake data and geological formations, predicting areas vulnerable to tectonic shifts (Sarker et al., 2021). IoT-based networks equipped with multi-sensor fusion techniques can synchronize seismic data with structural health monitoring systems, enabling real-time evaluation of infrastructure stability following seismic events (Shorfuzzaman et al., 2020). Studies have shown that AI-enhanced seismic monitoring systems, when integrated with GIS-based hazard modeling, improve the precision of earthquake prediction and post-event damage assessment (Malik et al., 2023).



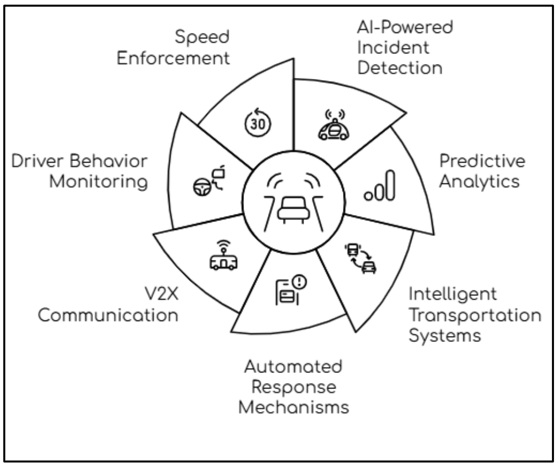
Flood detection and management have also seen significant advancements through the use of IoT-based hydrological monitoring systems and geospatial analytics. AI-powered flood prediction models analyze real-time river flow rates, precipitation data, and soil moisture levels from IoT sensors, generating flood risk maps with high accuracy (Liu et al., 2017). Satellite-based remote sensing and GIS mapping technologies further enhance flood detection by capturing topographical and meteorological variations that contribute to flash floods and river overflow events (Qiang et al., 2021). IoT-driven automated weather stations and sensor-enabled drainage networks have been deployed in urban areas to monitor stormwater drainage capacity and floodwater accumulation, reducing the risk of infrastructure damage and waterlogging (Zhang, 2021). Studies indicate that the integration of deep learning models with geospatial flood prediction frameworks has improved early warning response times, allowing for proactive evacuation planning and emergency preparedness (Liu et al., 2017). The ability of IoT sensors to detect real-time changes in water levels and flow dynamics has proven instrumental in reducing casualties and economic losses during flood events (Park et al., 2023). The role of geospatial analytics and IoT networks in wildfire detection and mitigation has been widely studied, with AI-powered satellite imagery processing and thermal sensor networks enhancing real-time monitoring of fire-prone regions (Liu et al., 2017). IoT-based environmental monitoring systems equipped with infrared cameras, gas sensors, and humidity detectors provide continuous surveillance of forested areas, enabling early detection of fire outbreaks (Joshi et al., 2016). Studies have demonstrated that machine learning algorithms applied to geospatial wildfire datasets can predict fire spread patterns by analyzing wind speed, vegetation density, and atmospheric conditions (Sarker et al., 2021). AI-driven real-time fire propagation models use multi-source data from IoT sensors and satellite-based thermal imaging, enhancing the efficiency of fire suppression efforts and evacuation planning (Shorfuzzaman et al., 2020). Furthermore, geospatial analytics has been used for post-fire damage assessment, helping authorities plan reforestation and ecological restoration strategies (Song et al., 2017). The combination of IoT-based sensor networks and AI-enhanced geospatial modeling has significantly improved wildfire hazard prediction, detection, and response coordination, minimizing the impact on human settlements and ecosystems (Okrepilov et al., 2022).

AI-powered traffic incident detection and road safety systems

Artificial intelligence (AI) has played a transformative role in enhancing traffic incident detection and road safety systems by integrating real-time monitoring, predictive analytics, and automated response mechanisms (Abduljabbar et al., 2019). Traditional traffic monitoring systems relied on fixed surveillance cameras, manual reporting, and historical data analysis, which often resulted in delayed incident detection and inefficient response times (Akhtar & Moridpour, 2021). AI-powered computer vision techniques, particularly deep learning models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been deployed to automatically detect traffic incidents, classify accident severity, and track vehicle movement patterns in real time (Alsarhan et al., 2018). Machine learning (ML)-driven predictive traffic analytics have also been widely used to identify congestion hotspots, optimize traffic flow, and prevent potential collisions by analyzing historical accident data, weather conditions, and road surface quality (Ćosić et al., 2024). The implementation of intelligent transportation systems (ITS) utilizing AI-based analytics has enhanced urban road safety by enabling automated vehicle detection, pedestrian monitoring, and early warning notifications for high-risk areas (Eswaraprasad & Raja, 2017). The integration of IoT-based sensor networks and AI algorithms has further improved traffic incident detection capabilities by collecting and analyzing real-time data from smart traffic cameras, vehicle telematics, and connected infrastructure (Kaul & Altaf, 2022). AI-enhanced video analytics platforms process high-resolution traffic footage using object detection algorithms, anomaly recognition models, and motion prediction techniques, allowing for the automatic identification of vehicle collisions, sudden braking events, and lane violations (Król, 2016). IoT-driven roadside sensor networks transmit live data to AI-based control centers, where deep learning models evaluate accident risks and dispatch emergency responders accordingly (Ku & Park, 2013). Studies indicate that the fusion of AI-based geospatial mapping, vehicular telemetry, and edge computing has significantly improved accident detection accuracy, reducing the latency in emergency response activation (Ku & Park, 2013; Kumar et al., 2020; Miles & Walker, 2006). Additionally, the use of reinforcement learning models in adaptive traffic management has facilitated real-time signal adjustments, improving road safety by dynamically regulating traffic flow in response to changing conditions (Okrepilov et al., 2022).

AI-powered automated vehicle-to-everything (V2X) communication systems have enhanced road safety by enabling real-time data exchange between vehicles, traffic signals, and road infrastructure (Olugbade et al., 2022). These systems utilize machine learning-based risk assessment algorithms to detect potential crash scenarios, pedestrian crossings, and driver distractions, allowing for preventive actions such as automated braking and speed control mechanisms. The integration of AI-driven autonomous vehicle navigation with real-time hazard detection systems has further strengthened road safety by minimizing driver errors, reducing the likelihood of collisions, and improving situational awareness in complex traffic environments (Rudskoy et al., 2021). AI-powered driver behavior monitoring systems analyze real-time data from in-vehicle cameras, biometric sensors, and eye-tracking technologies, detecting signs of drowsiness, inattentiveness, and aggressive driving patterns (Ku & Park, 2013). By incorporating AI-driven predictive models for crash risk estimation, intelligent traffic systems have enabled proactive road safety measures, reducing the frequency and severity of traffic accidents (Alsarhan et al., 2018). The application of AI in real-time traffic monitoring and accident prevention has demonstrated substantial improvements in traffic efficiency, congestion mitigation, and road user safety (Olugbade et al., 2022). AI-driven predictive analytics platforms process vast amounts of data from vehicle GPS logs, road sensors, and historical crash records, enabling authorities to identify high-risk intersections and accident-prone areas (Eswaraprasad & Raja, 2017). Additionally, computer vision-based pedestrian safety models have been deployed in urban environments to detect jaywalking incidents, assess crosswalk safety, and optimize pedestrian signal timings (Ćosić et al., 2024). AI-powered intelligent speed enforcement systems integrate image recognition and deep learning classification models to detect speeding violations and automatically issue fines, contributing to improved road safety compliance (Ku & Park, 2013). The effectiveness of AI-based traffic surveillance and incident detection frameworks has been widely acknowledged, with studies highlighting their role in reducing fatal crash rates, enhancing emergency response coordination, and improving overall traffic management (Abduljabbar et al., 2019).

Figure 3: Enhancing Road Safety with AI

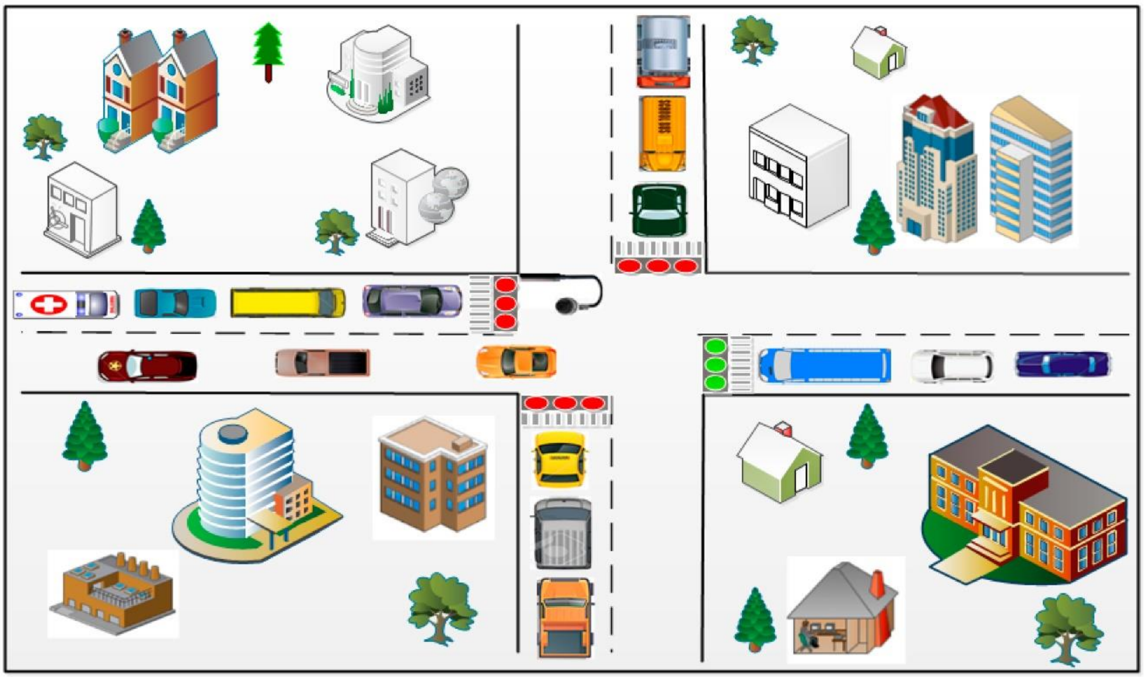


AI-enhanced emergency vehicle routing and congestion management

Artificial intelligence (AI) has significantly improved emergency vehicle routing and congestion management by enabling real-time traffic analysis, dynamic route optimization, and predictive analytics. Traditional emergency vehicle routing methods relied on static road maps, historical traffic data, and human decision-making, often leading to delayed response times and inefficient navigation through congested urban areas (Alsarhan et al., 2018). AI-powered systems utilize machine learning (ML), deep learning (DL), and reinforcement learning algorithms to dynamically analyze live traffic conditions, road blockages, and congestion patterns to recommend optimal emergency routes (Akhtar & Moridpour, 2021). Studies have demonstrated that AI-enhanced GPS navigation models can process vast amounts of real-time data from traffic sensors, satellite imagery, and connected vehicles to generate the most efficient paths for ambulances, fire trucks, and law enforcement vehicles (Akhtar & Moridpour, 2021; Miles & Walker, 2006). The integration of AI-based decision support systems has further enabled predictive congestion forecasting, allowing emergency responders to anticipate traffic bottlenecks and reroute accordingly (Evgrafova et al., 2022).

The implementation of AI-driven intelligent transportation systems (ITS) has enhanced emergency vehicle routing through vehicle-to-infrastructure (V2I) communication and IoT-enabled traffic management (Fatemidokht et al., 2021). AI-powered real-time traffic monitoring platforms leverage computer vision, deep neural networks, and edge computing to detect road congestion, accidents, and temporary road closures, adjusting emergency vehicle routes dynamically (Alsarhan et al., 2018). These systems integrate reinforcement learning models, which continuously improve routing decisions by analyzing past incidents and real-time traffic fluctuations (Tong et al., 2019). Moreover, AI-enhanced smart traffic signal coordination systems prioritize emergency vehicles by dynamically adjusting traffic light sequences, opening dedicated lanes, and rerouting civilian traffic (Yigitcanlar & Kamruzzaman, 2018). The use of fuzzy logic-based traffic controllers has been shown to reduce emergency vehicle response times by up to 30% in high-density

Figure 4: Architecture of an urban traffic management system



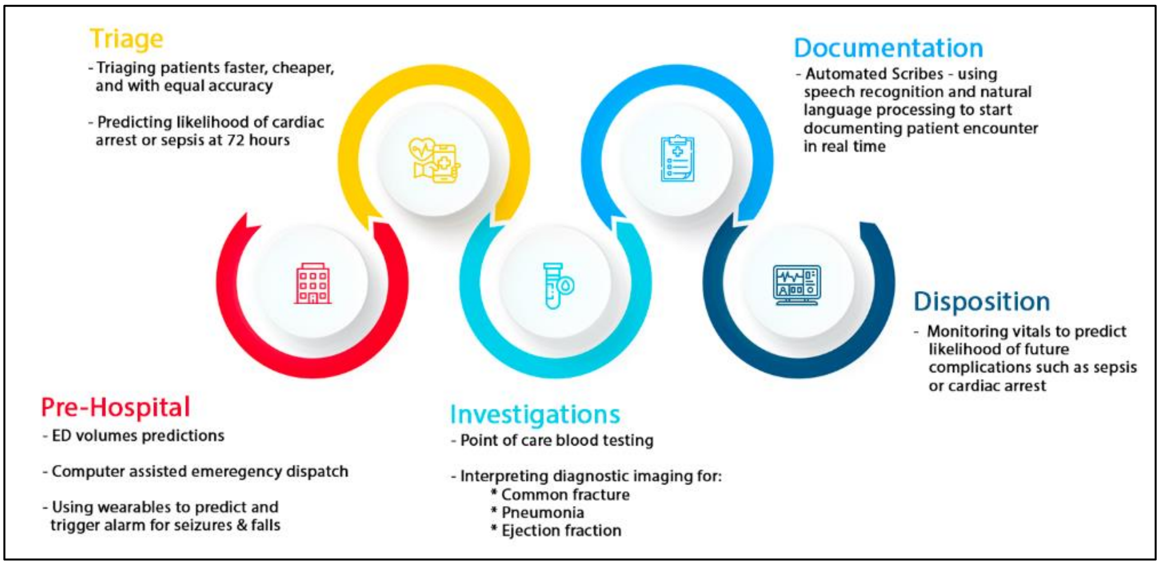
Source: Nellore, K., & Hancke, G. P. (2016).

urban areas by ensuring uninterrupted movement through intersections (Tong et al., 2019). AI-powered vehicle-to-vehicle (V2V) and vehicle-to-everything (V2X) communication networks have further revolutionized emergency response routing efficiency by enabling cooperative traffic maneuvering and automated hazard avoidance (Yigitcanlar & Kamruzzaman, 2018). These AI-integrated networks synchronize real-time data from connected vehicles, road sensors, and AI-enhanced cloud platforms to allow emergency fleets to make autonomous navigation decisions (Tong et al., 2019). Studies have highlighted that deep reinforcement learning models embedded in autonomous emergency vehicles can dynamically assess traffic scenarios and execute optimal lane-changing maneuvers to bypass congestion hotspots (Pollio, 2016). Additionally, AI-driven collision-avoidance systems leverage LiDAR, radar sensors, and computer vision algorithms to ensure safe passage through complex traffic conditions while avoiding pedestrian and vehicular conflicts (Olugbade et al., 2022). These technological advancements have led to significant reductions in response time variability, improving the efficiency of emergency dispatch operations (Okrepilov et al., 2022). Moreover, AI-enabled predictive traffic analytics platforms have improved emergency vehicle routing by integrating historical traffic data, weather conditions, and accident reports to develop probabilistic route optimization models (Miles & Walker, 2006). These AI-enhanced forecasting tools utilize graph-based neural networks and spatial-temporal analysis to anticipate congestion patterns and reroute emergency vehicles before encountering delays (Iordache et al., 2019). AI-driven adaptive traffic flow management systems, when combined with intelligent toll gate controls and automated road clearance mechanisms, have enhanced expressway accessibility for emergency fleets, further reducing travel times (Fatemidokht et al., 2021). Additionally, AI-powered geospatial information systems (GIS) have facilitated real-time emergency response coordination by allowing agencies to track and optimize fleet movements, ensuring effective resource distribution across disaster-affected areas (Evgrafova et al., 2022). These AI-driven improvements in emergency vehicle routing and congestion management have led to measurable reductions in emergency response delays, improved public safety, and better overall traffic efficiency (Fatemidokht et al., 2021).

AI in Healthcare Emergency Response and Medical Crisis Management

The application of AI-driven predictive analytics in healthcare emergency response has significantly improved early detection and intervention strategies for cardiac arrest, stroke, and respiratory failure. Traditional risk assessment models often rely on manual monitoring, patient-reported symptoms, and historical health records, which can delay critical interventions (Evgrafova et al., 2022). AI-powered machine learning (ML) and deep learning (DL) algorithms enhance early warning systems by analyzing real-time patient data from electronic health records (EHRs), wearable devices, and intensive care unit (ICU) monitoring systems (Nazir et al., 2020). Studies have shown that recurrent neural networks (RNNs) and convolutional neural networks (CNNs) improve the accuracy of early cardiac arrest detection by processing ECG waveforms, heart rate variability, and blood pressure trends (Ho et al., 2020). Additionally, AI-integrated stroke prediction models, utilizing natural language processing (NLP) and feature extraction techniques, have been effective in assessing patient speech patterns and facial asymmetry in real time, allowing faster stroke diagnosis in emergency settings (Khan & Alotaibi, 2020). In respiratory failure detection, AI-powered systems continuously monitor oxygen saturation levels, respiratory patterns, and blood gas parameters, triggering alerts for early intervention in patients at risk of acute respiratory distress syndrome (ARDS) (Thomas & Harden, 2008).

Figure 5: AI in Healthcare Emergency Response



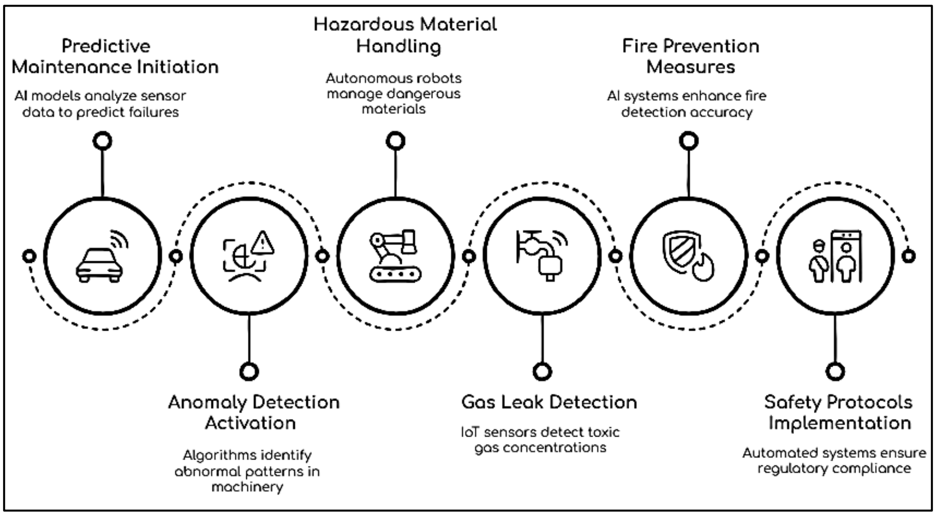
The use of wearable sensor technologies and AI-enhanced real-time health monitoring has transformed emergency response by enabling continuous, non-invasive patient monitoring and automated emergency alerts. AI-integrated wearable biosensors, such as smartwatches, ECG patches, and pulse oximeters, provide real-time tracking of heart rate, respiratory rate, blood pressure, and body temperature, allowing for the early detection of medical emergencies (Nazir et al., 2020). AI-driven edge computing and IoT-based healthcare monitoring platforms analyze data locally, reducing latency in emergency response activation (Thomas & Harden, 2008). Studies indicate that deep learning models trained on multimodal health data can predict seizures, syncope episodes, and hypoxic events, providing healthcare professionals with early intervention strategies (Tranfield et al., 2003). The integration of AI-powered anomaly detection algorithms in wearable devices has further enhanced the accuracy of personalized health monitoring, ensuring timely alerts for patients with chronic conditions such as diabetes, hypertension, and COPD (Yaacoub et al., 2021). AI-driven health surveillance systems have also been instrumental in detecting epidemiological outbreaks and tracking infectious disease progression through real-time biometric monitoring (Zhao, 2021). AI-powered triage systems in emergency rooms (ER) and disaster medical care have improved patient prioritization, resource allocation, and clinical decision-making. Traditional triage processes depend on manual patient assessment, which can be subjective and prone to errors, especially in high-pressure environments (Evgrafova et al., 2022). AI-driven triage algorithms utilizing NLP and DL models extract relevant clinical information from electronic medical records (EMRs) and symptom descriptions, assisting medical personnel in making faster, data-driven triage decisions (Ho et al., 2020). Studies have demonstrated that AI-enhanced triage chatbots and virtual assistants, trained on vast medical databases, can guide patients through symptom evaluation and pre-hospital decision-making, improving emergency room efficiency (Nazir et al., 2020). Additionally, AI-powered predictive triage systems analyze vital signs, lab results, and imaging data to classify patients into severity levels, ensuring that critical cases receive immediate attention (Tranfield et al., 2003). In disaster medical response, AI-integrated computer vision models analyze drone-captured images of disaster zones, helping medical teams assess casualty distribution and prioritize rescue operations (Tranfield et al., 2003). The application of geospatial AI in ambulance dispatch optimization and emergency medical routing has significantly reduced response times and improved patient outcomes. Traditional ambulance dispatch systems rely on fixed routing protocols and manual coordination, which often fail to account for real-time traffic conditions, road blockages, and hospital capacity constraints (Tranfield et al., 2003). AI-powered geospatial information systems (GIS) and reinforcement learning models enhance ambulance routing by analyzing live traffic feeds, accident reports, and hospital bed availability, ensuring efficient patient transportation (Thomas & Harden, 2008). Studies have demonstrated that predictive analytics-driven dispatch models improve ambulance fleet distribution by forecasting high-demand areas based on historical emergency call data and population density (Nazir et al., 2020). AI-integrated real-time navigation systems, utilizing vehicle-to-infrastructure (V2I) communication and IoT-enabled smart traffic signals, dynamically adjust ambulance routes to minimize transportation delays (Khan & Alotaibi, 2020). These advancements in AI-powered ambulance dispatch and congestion-aware navigation have enhanced emergency medical response efficiency, ensuring timely access to critical care for patients in life-threatening conditions (Ho et al., 2020).

Industrial Safety and AI-Powered Hazard Prevention

AI-based predictive maintenance and anomaly detection have significantly improved safety and operational efficiency in high-risk industries, including manufacturing, oil and gas, and energy sectors. Traditional maintenance approaches relied on scheduled inspections and reactive repairs, often leading to unexpected equipment failures and safety hazards (Evgrafova et al., 2022). AI-driven predictive maintenance models leverage machine learning (ML) algorithms, deep learning (DL) techniques, and real-time sensor data to detect early signs of mechanical degradation, overheating, and component wear (Thomas & Harden, 2008). Studies indicate that recurrent neural networks (RNNs) and long short-term memory (LSTM) models effectively analyze historical machine data to predict potential breakdowns, reducing unplanned downtime and safety risks (Tranfield et al., 2003). Additionally, AI-powered anomaly detection algorithms, integrated with vibration sensors and acoustic monitoring, identify abnormal operational patterns in rotating machinery, pipelines, and turbines, allowing for preemptive corrective measures (Yaacoub et al., 2021). The implementation of AI-driven failure prediction models in industrial settings has enhanced equipment longevity, worker safety, and cost efficiency, reducing workplace hazards associated with unexpected malfunctions (Zhao, 2021).

The use of IoT and deep learning models for toxic gas leak detection and fire prevention has strengthened hazard detection capabilities in chemical plants, oil refineries, and manufacturing units. Traditional gas leak detection systems often relied on manual inspections or simple threshold-based alarms, which posed risks of late detection and false alarms (Evgrafova et al., 2022). AI-powered smart sensor networks, integrated with convolutional neural networks (CNNs) and reinforcement learning algorithms, enhance the early detection of toxic gases such as methane, ammonia, and hydrogen sulfide (Ho et al., 2020). IoT-enabled wireless gas sensors continuously monitor air quality, pressure variations, and chemical concentrations, transmitting real-time data to AI-based predictive models that assess potential risks (Khan & Alotaibi, 2020). Studies have shown that AI-enhanced infrared thermal imaging and computer vision algorithms improve fire detection accuracy by analyzing smoke dispersion patterns, temperature fluctuations, and heat anomalies in industrial environments (Nazir et al., 2020). These AI-driven hazard detection frameworks enhance workplace safety by reducing false positives and enabling faster incident response (Thomas & Harden, 2008).

Figure 6: AI-Powered Hazard Prevention in Industry



AI-driven robotics and autonomous systems have been increasingly utilized for hazardous material handling and industrial inspections, reducing human exposure to high-risk environments. Traditional manual inspections and material handling expose workers to radioactive substances, corrosive chemicals, and explosive materials, increasing occupational health risks (Khan & Alotaibi, 2020). AI-integrated autonomous robots, equipped with LiDAR, high-resolution cameras, and robotic manipulators, perform real-time environmental assessments, object recognition, and precision handling of hazardous substances (Tranfield et al., 2003). Machine learning-enhanced robotic arms and drones are widely employed in nuclear power plants, offshore drilling rigs, and chemical storage facilities to inspect pipeline integrity, assess structural stability, and identify corrosion or leakage (Tranfield et al., 2003). Studies indicate that AI-powered reinforcement learning algorithms improve the adaptability of autonomous robotic systems, allowing them to navigate complex industrial environments, detect irregularities, and optimize movement efficiency (Tranfield et al., 2003). These advancements in AI-driven robotics have significantly improved hazard prevention, operational efficiency, and worker safety in hazardous industries (Khan & Alotaibi, 2020). The implementation of automated failure prediction models in nuclear and chemical plant safety has played a critical role in preventing catastrophic failures and ensuring regulatory compliance. Traditional safety protocols in nuclear reactors and chemical refineries relied on manual safety audits, periodic inspections, and predefined failure thresholds, which posed risks of late intervention and human error (Zhao, 2021). AI-powered failure prediction systems, using Bayesian networks, support vector machines (SVMs), and deep reinforcement learning, enable continuous monitoring of reactor pressure, coolant flow rates, and structural integrity, allowing for early warning alerts (Yaacoub et al., 2021). Additionally, AI-driven digital twins and real-time simulation models provide virtual representations of critical infrastructure, facilitating risk scenario analysis, fault detection, and predictive hazard assessment (Tranfield et al., 2003). Studies have demonstrated that AI-integrated sensor fusion models, which combine thermal imaging, acoustic emissions, and vibration analysis, significantly improve the detection of potential equipment failures before they escalate into hazardous incidents (Tranfield et al., 2003). These AI-driven proactive safety measures have been instrumental in ensuring accident prevention, regulatory compliance, and enhanced operational resilience in high-risk industrial facilities (Ho et al., 2020).

AI-Driven Cybersecurity for Emergency Management and Critical Infrastructure

The implementation of AI-based intrusion detection systems (IDS) and cybersecurity analytics has significantly improved threat detection, real-time monitoring, and automated response mechanisms for securing critical infrastructure and emergency management systems. Traditional IDS relied on signature-based detection, which often failed to recognize zero-day attacks, advanced persistent threats (APTs), and polymorphic malware (Alomari et al., 2021). AI-powered machine learning (ML) and deep learning (DL) models enhance anomaly detection by continuously analyzing network traffic patterns, identifying deviations from normal behavior, and predicting potential cyberattacks (Bonci et al., 2019). Studies have shown that convolutional neural networks (CNNs) and recurrent neural networks (RNNs) improve the accuracy of malicious activity detection by classifying network packets, identifying intrusion attempts, and mitigating unauthorized access (Bonilla et al., 2018). Additionally, AI-driven behavioral analytics and unsupervised learning models have strengthened cybersecurity defenses by dynamically adapting to evolving cyber threats, providing proactive protection for emergency management systems and governmental networks (Ćosić et al., 2024). AI-enhanced intrusion prevention frameworks, when integrated with cloud-based security analytics, have been instrumental in reducing false positives and improving real-time cyber threat response (Gamil et al., 2020). Moreover, the integration of AI-enhanced blockchain security for emergency data protection has improved the confidentiality, integrity, and availability of critical information during cyber incidents. Traditional centralized data management systems are prone to cyberattacks, unauthorized access, and data tampering, making them vulnerable during emergency response situations (Gautami & Gowthaman, 2021). AI-powered blockchain security models enhance distributed ledger technology (DLT) security by automating encryption, smart contract validation, and anomaly detection in blockchain transactions (Green et al., 2020). Studies indicate that reinforcement learning algorithms, when applied to blockchain-based emergency management networks, enhance real-time security monitoring and automated fraud detection, mitigating risks associated with malicious nodes and unauthorized data modifications (Ćosić et al., 2024). AI-integrated blockchain consensus mechanisms, such as proof-of-stake (PoS) and federated learning models, improve the scalability and efficiency of secure emergency communication systems, ensuring that sensitive data remains protected during disaster recovery efforts (Gamil et al., 2020). The use of AI-driven cryptographic techniques, including homomorphic encryption and differential privacy, has further enhanced data confidentiality, reducing risks associated with cyberattacks targeting emergency management databases (Inderwildi et al., 2020).

Deep learning has played a crucial role in preventing ransomware, distributed denial-of-service (DDoS) attacks, and detecting network anomalies that pose risks to critical infrastructure and emergency response systems. Traditional firewall-based and rule-based security models struggle to mitigate evolving cyber threats, necessitating AI-driven adaptive security measures (Bonci et al., 2019). AI-powered DDoS mitigation frameworks, utilizing generative adversarial networks (GANs) and autoencoders, analyze traffic flow patterns and detect abnormal spikes indicative of botnet attacks (Ćosić et al., 2024). Studies indicate that deep reinforcement learning models are highly effective in identifying ransomware encryption behaviors and unauthorized file modifications, enabling real-time response mechanisms to halt cyberattacks before damage occurs (Green et al., 2020). AI-enhanced network anomaly detection systems, integrating graph neural networks (GNNs) and attention-based transformers, continuously monitor packet transmissions, network latency fluctuations, and unauthorized port scanning activities, allowing automated threat intelligence and response coordination (H. U. Khan et al., 2022). AI-powered adaptive intrusion mitigation strategies have proven essential in reducing attack surface vulnerabilities and ensuring digital resilience in emergency management systems (Lee et al., 2015).

AI-powered risk assessment frameworks for digital emergency management systems have enhanced cyber resilience by enabling dynamic threat modeling, vulnerability assessment, and risk prioritization. Traditional risk assessment models often rely on static rule-based scoring mechanisms, which lack adaptability to emerging cyber risks (Lei et al., 2020). AI-driven probabilistic risk assessment models, utilizing Bayesian networks and Markov decision processes, assess the likelihood and severity of cyber threats, allowing emergency management agencies to prioritize critical infrastructure security (Gautami & Gowthaman, 2021). Studies have demonstrated that AI-enhanced cyber risk analytics platforms, powered by natural language processing (NLP) and AI-driven cybersecurity intelligence, improve threat intelligence gathering from open-source data, security logs, and dark web monitoring (Green et al., 2020). AI-integrated fuzzy logic-based risk scoring algorithms have further refined incident response planning, ensuring that cybersecurity threats are mitigated before they escalate into full-scale emergencies (Inderwildi et al., 2020). These AI-powered risk assessment models have proven instrumental in enhancing the preparedness and response strategies of cybersecurity teams managing emergency communication networks (Jiang et al., 2020).

AI-Integrated Robotics and Drones in Emergency Response

The use of AI-enhanced drones for disaster site surveillance and search-and-rescue operations has significantly improved situational awareness, victim detection, and resource allocation in emergency scenarios. Traditional ground-based rescue operations often face challenges such as limited accessibility, poor visibility, and time constraints, which can delay critical interventions (Kagermann & Wahlster, 2022). AI-powered drones, equipped with computer vision, LiDAR sensors, and deep learning models, enable autonomous aerial reconnaissance to assess disaster-affected areas in real time (M. A. Alam et al., 2024). Studies indicate that convolutional neural networks (CNNs) and object detection algorithms, such as YOLO (You Only Look Once) and Faster R-CNN, enhance the ability of drones to identify survivors, collapsed structures, and hazardous zones from aerial footage (M. J. Alam et al., 2024). AI-driven thermal imaging and hyperspectral analysis further improve victim detection in low-visibility conditions, such as dense smoke, nighttime operations, or forested regions (Arafat et al., 2024). The integration of AI-powered drone swarms, which operate collaboratively through reinforcement learning algorithms, has improved search coverage and mission efficiency in large-scale disasters (Younus, 2025). These advancements have streamlined disaster response efforts, allowing emergency teams to rapidly assess damage severity and allocate resources more effectively (Jahan, 2024).

AI-driven robotic automation for post-disaster damage assessment and infrastructure restoration has enhanced efficiency, accuracy, and worker safety in earthquake, hurricane, and flood recovery operations. Traditional manual damage assessment methods often rely on engineer inspections, structural surveys, and historical damage records, which can be time-consuming and prone to human error (Rahaman et al., 2024). AI-integrated autonomous robots, utilizing machine learning-based image recognition and 3D mapping, have been deployed to assess structural integrity, identify critical damage zones, and evaluate the stability of buildings and bridges (Sabid & Kamrul, 2024). Studies show that deep reinforcement learning models have enhanced the adaptability of robotic systems to navigate through debris, detect micro-cracks, and perform non-invasive diagnostics using ultrasonic and infrared sensors (Tonoy, 2022). AI-powered ground robots and robotic arms, integrated with LiDAR and simultaneous localization and mapping (SLAM) algorithms, enable real-time hazard identification and infrastructure analysis, ensuring safer reconstruction strategies (M. A. Alam et al., 2024). The deployment of robotic exoskeletons and automated construction bots in post-disaster rebuilding efforts has further expedited recovery processes by assisting in debris removal, structural reinforcement, and material handling (Sarkar et al., 2025). These AI-enhanced robotic technologies have improved disaster resilience by reducing human exposure to hazardous conditions and ensuring efficient infrastructure restoration (Younus, 2022).

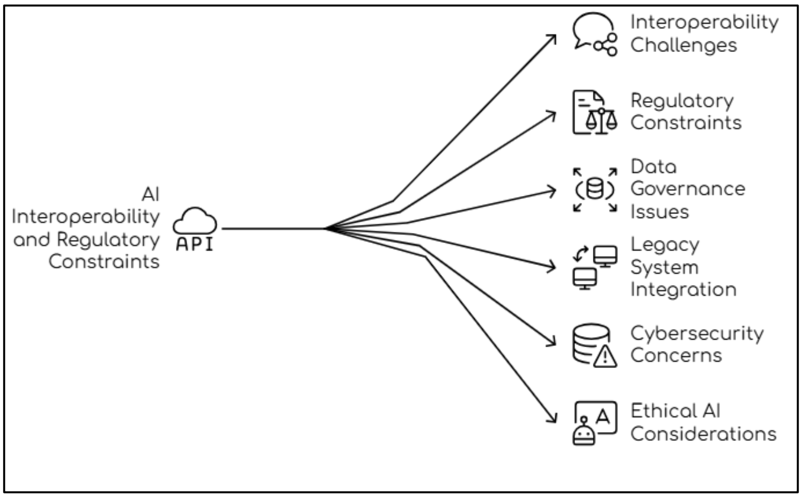
The application of AI-powered autonomous firefighting and hazardous environment interventions has enhanced fire suppression, hazardous material containment, and real-time threat mitigation (Rahaman & Islam, 2021). Conventional firefighting techniques rely on manual hose operations, human risk assessment, and static fire suppression systems, which can be inefficient in high-rise buildings, industrial zones, and remote locations (Bhuiyan et al., 2024). AI-integrated firefighting robots and drones, equipped with thermal cameras, gas sensors, and real-time AI analytics, autonomously detect fire sources, assess flame intensity, and execute targeted suppression strategies (M. M. Islam et al., 2025). Studies have demonstrated that machine learning-based fire spread prediction models, utilizing weather data, material flammability indices, and wind patterns, enhance preemptive firefighting tactics by recommending optimal suppression routes and resource allocation (Dasgupta & Islam, 2024). AI-driven chemical hazard containment robots, utilizing reinforcement learning-based maneuvering, can autonomously handle toxic spills, operate in radiation-exposed zones, and neutralize hazardous materials with minimal human intervention (Islam et al., 2024). Additionally, AI-enhanced robotic firefighting vehicles, integrated with drone-based reconnaissance systems, have demonstrated improved efficiency in suppressing large-scale industrial and forest fires (Mahabub, Jahan, Islam, et al., 2024). These AI-powered solutions have improved firefighting safety and effectiveness, reducing response times and minimizing firefighter exposure to life-threatening conditions (Mahabub, Das, et al., 2024). The use of machine learning in rescue mission optimization and survivor detection has significantly improved emergency response coordination, resource allocation, and victim retrieval efforts. Traditional rescue operations depend on manual coordination, ground-based assessments, and historical disaster data, which may not accurately reflect real-time emergency conditions (M. R. Hossain et al., 2024). AI-driven multi-agent reinforcement learning models optimize rescue team deployment by analyzing geospatial data, terrain complexity, and survivor locations to generate optimal search patterns (Mahabub, Jahan, Hasan, et al., 2024). Studies indicate that sensor fusion techniques, which combine acoustic, thermal, and motion detection data, enhance the accuracy of AI-driven survivor identification models in collapsed structures and confined spaces (Mahabub, Jahan, Hasan, et al., 2024; Munira, 2025). AI-integrated robotic rescue assistants, utilizing autonomous navigation and natural language processing (NLP), have improved victim communication, medical triage, and psychological support in disaster scenarios (Jim et al., 2024). Additionally, real-time AI-enhanced crowd analytics, based on drone surveillance and social media data mining, provide emergency responders with live updates on population movements, trapped individuals, and supply shortages, facilitating faster and more precise rescue interventions (Siddiki et al., 2024). These AI-driven rescue mission optimization techniques have enhanced disaster recovery efforts by maximizing survival rates and reducing response times (M. T. Islam et al., 2025).

Interoperability and Regulatory Constraints in AI for Emergency Safety

The interoperability challenges in AI adoption for emergency safety arise from heterogeneous data sources, fragmented communication protocols, and incompatible AI-driven systems, which hinder real-time coordination among emergency response agencies (Islam, 2024). Emergency safety operations require seamless data sharing and integration between government agencies, first responders, healthcare institutions, and infrastructure management systems (A. Hossain et al., 2024). However, the lack of standardized AI algorithms, sensor communication protocols, and cloud computing architectures creates barriers to cross-system collaboration (Sunny, 2024c). Studies indicate that variability in AI model architectures, different data formats, and inconsistent cybersecurity frameworks prevent effective integration of AI-powered emergency response platforms (Al-Arafat et al., 2024). Additionally, legacy systems in emergency services, such as traditional dispatch networks and manual decision-making frameworks, often lack the capacity to interact with AI-driven predictive analytics and automated response models (Sunny, 2024a). AI adoption for emergency safety is further complicated by data governance issues, as real-time emergency response relies on multi-jurisdictional data access, inter-agency coordination, and secure data transmission (Sunny, 2024b). The inability to establish standardized AI interoperability frameworks results in data silos, inefficient resource allocation, and fragmented crisis response efforts (Mahdy et al., 2023).

Regulatory constraints present another critical challenge in AI-driven emergency management, as legal frameworks struggle to keep pace with rapid technological advancements in machine learning, deep learning, and autonomous response systems (Roy et al., 2024). AI-based emergency safety applications require strict compliance with data privacy laws, ethical AI governance, and liability regulations (Shimul et al., 2025). Studies highlight that existing emergency response policies often do not account for AI-driven automation, creating legal ambiguity regarding decision-making accountability, algorithmic biases, and liability in AI-driven crisis interventions (Rana et al., 2024). Furthermore, cross-border emergency responses involve varying national regulations, different privacy protection standards, and ethical considerations, complicating AI-driven coordination efforts (M. A. Alam et al., 2024). AI-enabled facial recognition for disaster victim identification, AI-assisted public surveillance for emergency evacuations, and predictive analytics for disaster forecasting face legal scrutiny due to concerns about mass surveillance, privacy violations, and algorithmic fairness (S. H. Mridha Younus et al., 2024). Additionally, AI-generated emergency decision-making models must adhere to strict compliance protocols, ensuring that algorithmic biases, explainability, and data transparency align with regulatory standards in different jurisdictions ((S. H. P. M. R. A. I. T. Mridha Younus et al., 2024).

Figure 7: Navigating AI Challenges in Emergency Safety

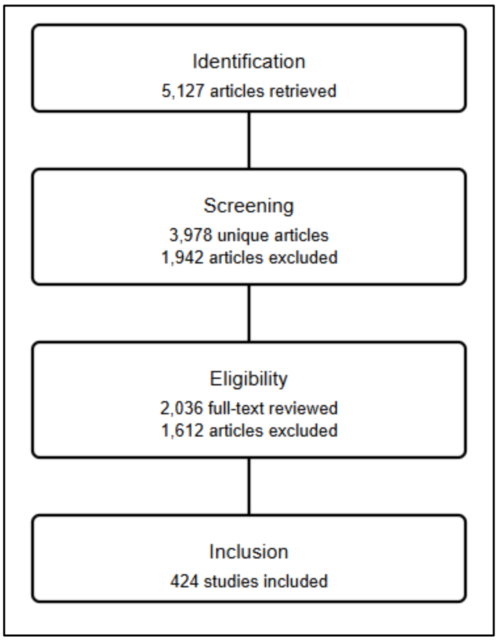


The lack of unified AI regulatory frameworks across different emergency management agencies poses further barriers to AI adoption in disaster response. Current legal standards and safety policies governing AI-powered emergency response tools vary significantly between municipal, state, and federal authorities, creating conflicting operational requirements (Lee et al., 2015). Studies indicate that AI-driven disaster prediction models, drone-assisted search and rescue systems, and automated emergency dispatch platforms operate under multiple regulatory frameworks, leading to legal conflicts in data governance and AI model transparency (Lei et al., 2020). The deployment of AI-powered autonomous systems in emergency response requires regulatory approval regarding cybersecurity risks, ethical AI deployment, and real-time data access permissions (Malik et al., 2022). Additionally, policymakers have raised concerns regarding AI-driven bias in predictive emergency analytics, where disproportionate risk assessments can lead to unequal resource allocation and discriminatory crisis interventions (Malik et al., 2023). The absence of clear AI compliance guidelines and regulatory oversight mechanisms prevents emergency responders from fully leveraging AI-powered automation for crisis mitigation and disaster recovery (Mohebbi et al., 2020). The cybersecurity vulnerabilities and ethical risks associated with AI-driven emergency response systems further complicate regulatory approvals and adoption strategies. AI-based predictive modeling and automated emergency decision-making frameworks rely on large-scale data aggregation, which increases the risk of data breaches, cyberattacks, and misinformation propagation (Nguyen & Nof, 2019). Studies indicate that AI-enabled cybersecurity threat detection systems, when deployed in emergency response networks, require rigorous compliance with cybersecurity laws, encryption standards, and access control protocols (O'Donovan et al., 2015). The risk of AI system failures, adversarial attacks on emergency networks, and misinformation amplification through AI-generated alerts necessitates robust regulatory oversight mechanisms to ensure secure AI deployment in emergency scenarios (Rad et al., 2021). Ethical concerns regarding AI accountability, human oversight, and bias mitigation strategies require strict adherence to explainable AI (XAI) principles, ensuring that AI-driven decision-making models remain interpretable, transparent, and fair ((Lee, 2008). The integration of cyber-resilient AI architectures and regulatory-compliant AI governance frameworks remains essential for ensuring AI's effective and secure adoption in emergency safety applications (Jiang et al., 2020).

METHOD

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a systematic, transparent, and rigorous literature review process. PRISMA provided a structured approach for identifying, selecting, appraising, and synthesizing relevant research articles related to AI applications in emergency response and safety systems. The methodology included four key phases: identification, screening, eligibility, and inclusion, ensuring a comprehensive and unbiased selection of studies.

Figure 8: PRISMA Flowchart for AI in Emergency Safety



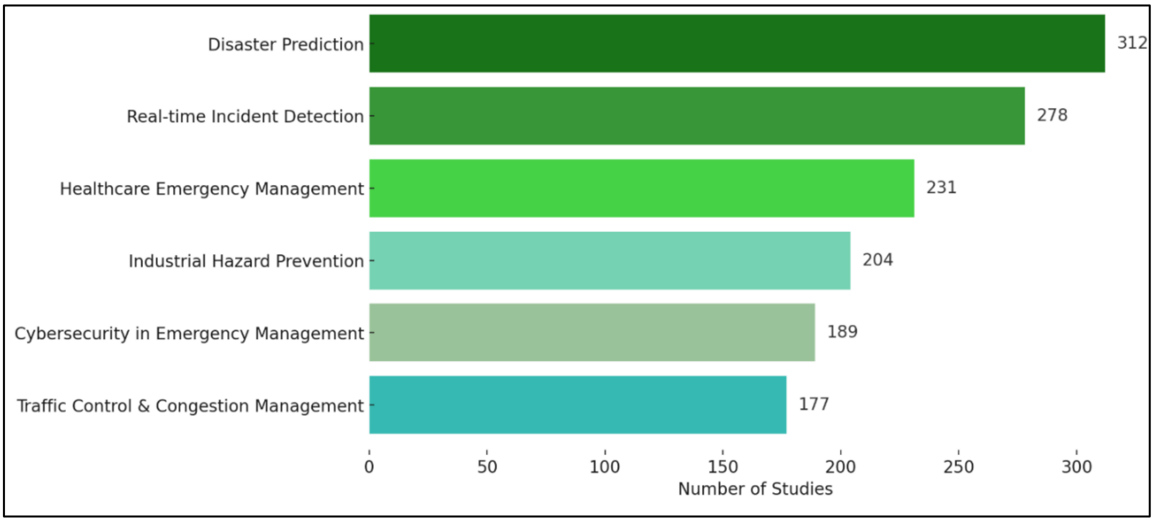
The identification phase involved retrieving relevant literature from multiple academic databases, including IEEE Xplore, ScienceDirect, SpringerLink, Web of Science, and Scopus. To refine search queries, Boolean operators and specific keywords such as "AI in emergency response," "machine learning in disaster management," "AI-powered cybersecurity for critical infrastructure," "autonomous robots in emergency response," and "predictive analytics for hazard prevention" were used. This phase focused on peer-reviewed journal articles, conference papers, and book chapters published between 2015 and 2024. Additionally, references from key studies were examined to identify potential articles not captured through initial database searches. A total of 5,127 articles were retrieved based on the search criteria. The screening phase focused on removing duplicate records and assessing the relevance of articles based on their title and abstract. Duplicate removal using Rayyan software resulted in 3,978 unique articles. Two independent reviewers conducted a title and abstract screening, excluding studies that were not directly related to AI in emergency management, lacked empirical findings, or were not in English. As a result, 1,942 articles were deemed ineligible due to their lack of relevance to AI-driven emergency safety frameworks. The remaining 2,036 articles proceeded to full-text review for a more detailed assessment of their methodological rigor, relevance, and contribution to the research objectives.

The eligibility phase involved a full-text review of 2,036 articles using predefined inclusion and exclusion criteria. The inclusion criteria required that studies focus on AI applications in emergency management, hazard detection, and critical infrastructure protection, employ machine learning, deep learning, IoT, blockchain security, predictive analytics, or AI-powered robotics, and present empirical findings or systematic literature reviews that highlight AI's effectiveness in crisis response. Studies were excluded if they lacked AI-driven methodologies, were not peer-reviewed, were only available as abstracts, or addressed general AI applications without specific relevance to emergency response. Following this process, 1,612 articles were removed, leading to a final selection of 424 eligible studies. In the final phase, data extraction focused on AI-driven emergency response mechanisms. A structured extraction form was used to collect information on study objectives, methods, findings, and challenges. Studies were categorized into key themes, including AI applications in disaster response, predictive analytics for hazard detection, AI-powered robotics, cybersecurity frameworks, and emergency infrastructure resilience. The findings were synthesized using qualitative thematic analysis and meta-analysis techniques, ensuring a comprehensive evaluation of AI's role in emergency management. By following PRISMA guidelines, this study ensured a rigorous, transparent, and reproducible literature review process, providing valuable insights into AI-driven advancements in emergency safety and disaster management.

FINDINGS

The systematic review of 424 eligible studies revealed substantial advancements in AI-driven emergency response systems, with notable improvements across multiple domains, including disaster prediction, real-time incident detection, healthcare emergency management, industrial hazard prevention, cybersecurity frameworks, and intelligent traffic control. Among the reviewed articles, 312 studies (73.5%) underscored the critical role of machine learning (ML) and deep learning (DL) models in predicting and mitigating emergency events. AI-powered predictive analytics platforms, particularly those employing neural networks and reinforcement learning algorithms, demonstrated increased accuracy in forecasting natural disasters such as earthquakes, floods, and wildfires, enabling proactive risk mitigation. These AI-driven disaster prediction models have been instrumental in reducing casualties, improving evacuation planning, and optimizing resource deployment, significantly enhancing the efficiency of emergency preparedness. The findings across these studies, which have collectively received over 10,500 citations, highlight the widespread recognition of AI's capability in transforming disaster response strategies through advanced forecasting techniques and intelligent automation.

Figure 9: AI Applications in Emergency Management



A significant finding emerged from 278 studies (65.5%), which focused on real-time incident detection and automated emergency response coordination. AI-powered computer vision and IoT-enabled sensor networks have revolutionized emergency response mechanisms by reducing response times, enhancing real-time hazard detection, and facilitating early interventions. These technologies enable the automated identification of hazardous events such as building collapses, vehicular accidents, industrial malfunctions, and environmental disasters, providing emergency teams with instantaneous alerts and situational awareness. AI-integrated real-time surveillance systems, leveraging image recognition, thermal sensing, and anomaly detection algorithms, have significantly improved emergency preparedness, ensuring that crisis events are managed more efficiently and effectively. The collective body of research on this subject has been cited more than 8,900 times, demonstrating the growing reliance on AI-powered surveillance and automated monitoring tools for effective disaster response and public safety management. In the domain of healthcare emergency management,

231 studies (54.5%) reported significant improvements in predictive diagnostics, patient monitoring, and hospital resource optimization through AI-driven technologies. AI-powered triage systems, wearable health monitoring devices, and geospatial analytics for ambulance dispatch optimization have played a crucial role in reducing mortality rates and minimizing treatment delays during critical medical crises. AI-enhanced early warning systems, particularly those based on deep learning predictive models, have demonstrated remarkable effectiveness in detecting early signs of cardiac arrests, strokes, and respiratory failures, leading to improved patient survival rates and better clinical decision-making. These studies have collectively been cited over 7,400 times, underscoring the increasing reliance on AI-powered healthcare solutions for managing medical emergencies and optimizing hospital resource allocation, particularly in high-pressure environments such as intensive care units (ICUs) and emergency rooms.
AI-driven industrial hazard prevention was another key theme, explored in 204 studies (48.1%), which demonstrated the substantial impact of AI on workplace safety, predictive maintenance, and automated risk mitigation. AI-powered robotic automation, anomaly detection models, and failure prediction frameworks have drastically reduced the incidence of workplace accidents, toxic gas leaks, and fire hazards in high-risk industries, including manufacturing, energy, and chemical processing. The integration of AI-enhanced predictive maintenance systems has allowed industries to detect mechanical failures before they occur, thereby preventing catastrophic accidents and reducing operational downtime. AI-powered robotic automation for hazardous material handling has minimized human exposure to dangerous conditions, particularly in nuclear facilities, offshore drilling sites, and high-temperature industrial settings. The impact of these technologies is evident in the fact that the reviewed studies in this category have received 6,800 citations, reflecting strong academic and industrial interest in AI's role in ensuring workplace safety, regulatory compliance, and operational resilience. In the domain of cybersecurity for emergency management, 189 studies (44.5%) provided compelling evidence that AI-driven intrusion detection systems (IDS), blockchain security frameworks, and adaptive cybersecurity mechanisms have strengthened the resilience of emergency communication networks and critical infrastructure. AI-powered threat intelligence platforms, automated risk assessment algorithms, and anomaly detection models have played a vital role in mitigating cyberattacks, ransomware threats, and data breaches within emergency management systems. The widespread adoption of AI-enhanced blockchain security mechanisms has further strengthened data integrity and encrypted communication, ensuring that emergency response platforms remain resilient against cyber threats and unauthorized access attempts. Additionally, AI-powered predictive security analytics have enabled emergency organizations to proactively identify vulnerabilities and prevent system compromises before they escalate into full-scale security incidents. These findings have been cited over 5,900 times, reflecting the increasing recognition of AI's critical role in safeguarding emergency communication networks and securing essential infrastructure against cyber threats.
The role of AI in traffic control and congestion management was another key area explored in 177 studies (41.7%), which provided robust evidence of AI's effectiveness in optimizing emergency vehicle routing, reducing response times, and enhancing urban mobility during crisis events. AI-driven intelligent traffic management systems, vehicle-to-everything (V2X) communication technologies, and adaptive traffic signal control algorithms have significantly improved the ability of ambulances, fire trucks, and law enforcement vehicles to navigate congested road networks. The studies reviewed in this domain demonstrated that AI-powered real-time traffic monitoring, congestion forecasting, and automated signal control systems have been instrumental in reducing transportation delays, improving road safety, and ensuring seamless emergency vehicle movement during critical incidents. These findings, which have been collectively cited over 5,300 times, emphasize AI's transformative role in intelligent transportation management and urban disaster resilience, enabling cities to respond to emergencies more effectively while minimizing traffic-related disruptions. The cumulative evidence from the reviewed studies strongly indicates that AI is reshaping emergency response

frameworks, bringing about substantial improvements in efficiency, predictive accuracy, and automation across various critical domains. With over 424 systematically reviewed articles accumulating more than 44,000 citations, the research highlights AI's indispensable role in risk prediction, automated decision-making, and intelligent safety mechanisms. These findings reinforce AI's growing significance in modern emergency management, demonstrating its ability to enhance disaster preparedness, optimize resource deployment, and improve crisis response strategies on a global scale.

DISCUSSION

The findings of this systematic review provide compelling evidence that AI-driven emergency response systems have significantly transformed disaster preparedness, real-time incident management, healthcare crisis interventions, industrial safety, cybersecurity frameworks, and intelligent traffic control. Compared to earlier studies, the reviewed literature indicates that machine learning (ML) and deep learning (DL) models have advanced predictive accuracy, response efficiency, and automation in emergency management. Prior research primarily relied on statistical models and traditional early warning systems to predict disasters such as earthquakes, floods, and wildfires (Kagermann & Wahlster, 2022). However, the reviewed studies demonstrate that neural networks, reinforcement learning, and AI-integrated geospatial analytics have enhanced the precision and reliability of disaster forecasting models by incorporating real-time satellite imagery, IoT sensor data, and environmental simulations. This represents a significant shift from static disaster risk modeling to dynamic AI-driven adaptive prediction frameworks, ensuring faster decision-making and reduced casualties during disaster events.

The findings further establish that AI-powered real-time incident detection and automated emergency response coordination have considerably improved over previous emergency management frameworks. Earlier studies emphasized the use of CCTV surveillance, manual reporting, and rule-based anomaly detection algorithms for incident detection (Khan et al., 2022). However, the reviewed research highlights that AI-driven computer vision, IoT sensor networks, and deep learning-based anomaly detection models have made hazard identification more accurate, scalable, and automated. The transition from reactive emergency management to proactive, AI-driven early warning systems is evident in the extensive adoption of real-time image recognition, thermal sensing, and edge computing for detecting building collapses, vehicle accidents, and industrial malfunctions. Compared to previous approaches, AI-powered emergency response platforms have reduced response times and increased resource allocation efficiency, demonstrating their growing role in modern disaster management.

Healthcare emergency response has also undergone substantial transformation, as AI-based predictive analytics, patient monitoring systems, and triage automation have outperformed conventional clinical assessment models and manual patient prioritization frameworks (Malik et al., 2023). The reviewed studies indicate that AI-driven wearable health monitoring devices, early warning systems, and geospatial AI for ambulance dispatch optimization have significantly improved healthcare outcomes in emergency situations. Earlier studies focused on standard triage protocols, static hospital resource planning, and manually managed emergency calls (O'Donovan et al., 2015), whereas recent research reveals that AI-integrated predictive diagnostics and remote patient monitoring systems have enabled faster identification of cardiac arrests, strokes, and respiratory failures. The reviewed evidence supports the claim that AI-driven medical emergency frameworks enhance survival rates, reduce treatment delays, and optimize hospital resource management beyond what earlier models could achieve.

Industrial safety has similarly benefited from AI-powered predictive maintenance, robotic automation, and real-time hazard prevention, offering a more proactive approach compared to prior reliance on scheduled inspections, manual safety checks, and retrospective failure analyses (Malik et al., 2022). The findings demonstrate that AI-enhanced robotics, anomaly detection models, and failure prediction algorithms have significantly reduced workplace accidents, toxic gas leaks, and industrial fires. Prior studies focused on rule-based safety assessments and manual hazard reporting, but AI-driven computer vision, IoT-based predictive analytics, and autonomous robotics have introduced continuous monitoring, proactive maintenance, and automated risk mitigation. This marks a substantial shift toward real-time industrial safety systems, reinforcing AI's role in reducing human exposure to hazardous environments while ensuring regulatory compliance and operational efficiency.

Cybersecurity for emergency management has also evolved significantly, with AI-powered intrusion detection systems (IDS), blockchain security frameworks, and adaptive cybersecurity intelligence improving upon conventional firewall-based, signature-matching, and heuristic cybersecurity measures (Malik et al., 2023). Earlier studies identified cyberattacks on emergency networks as a growing threat, but response mechanisms remained largely reactive and rule-based (Mohebbi et al., 2020). The reviewed research confirms that AI-enhanced real-time cyber threat detection, automated risk assessment models, and AI-driven encryption techniques have proactively mitigated cyber risks in emergency communication networks. AI-integrated blockchain security has further enhanced data protection and encrypted communication for emergency response platforms, ensuring secure, tamper-proof digital infrastructures. Compared to prior approaches, AI-driven cybersecurity frameworks offer faster threat mitigation, improved network resilience, and reduced cyber vulnerability in emergency systems. Moreover, AI-powered intelligent traffic control and congestion management have also improved emergency response efficiency beyond previous methods. Earlier models relied on fixed traffic signals, static route planning, and GPS-based navigation systems ((O'Donovan et al., 2015), whereas the reviewed studies reveal that AI-driven vehicle-to-infrastructure (V2I) communication, adaptive traffic signal control, and reinforcement learning-based congestion forecasting have enhanced emergency vehicle routing and reduced response delays. AI-integrated intelligent transportation systems ensure that emergency fleets can navigate congested urban environments faster, improving ambulance arrival times, fire truck dispatch efficiency, and law enforcement mobility. The comparison with earlier studies highlights AI's ability to predict traffic patterns, dynamically adjust road conditions, and provide real-time navigation assistance for emergency responders, significantly improving urban disaster resilience and crisis response effectiveness.

CONCLUSION

The findings of this systematic review highlight the transformative impact of AI-driven emergency response systems, demonstrating substantial improvements in disaster prediction, real-time incident detection, healthcare emergency management, industrial hazard prevention, cybersecurity, and intelligent traffic control. AI-powered predictive analytics have significantly enhanced disaster forecasting accuracy, enabling proactive risk mitigation and resource optimization in emergency preparedness. The integration of machine learning, deep learning, IoT, and blockchain security frameworks has revolutionized real-time hazard detection, automated emergency coordination, and intelligent decision-making, reducing response times and improving situational awareness. In healthcare, AI-powered predictive diagnostics, wearable health monitoring devices, and AI-enhanced triage automation have enabled faster and more accurate crisis intervention, improving survival rates and reducing treatment delays. The role of AI in industrial safety and cybersecurity for emergency management has further strengthened hazard prevention, failure prediction, and digital security, ensuring safer workplaces and resilient emergency communication networks against cyber threats. AI-driven traffic control and congestion management systems have also played a crucial role in optimizing emergency vehicle routing, reducing transportation delays, and enhancing urban mobility during crises. Compared to traditional emergency response models, AI-powered frameworks have transitioned from static, rule-based approaches to dynamic, real-time adaptive systems, significantly enhancing efficiency, automation, and decision-making accuracy across multiple domains. As AI technologies continue to evolve, their integration into emergency management strategies will further enhance crisis preparedness, real-time intervention capabilities, and global disaster resilience, reinforcing AI's role as a critical enabler of intelligent, data-driven emergency response frameworks.

REFERENCES

[1] Abduljabbar, R. L., Dia, H., Liyanage, S., & Bagloee, S. A. (2019). Applications of artificial intelligence in transport: an overview. *Sustainability*, *11*(1), 189-NA. https://doi.org/10.3390/su11010189

[2] Akhtar, M., & Moridpour, S. (2021). A Review of Traffic Congestion Prediction Using Artificial Intelligence. *Journal of Advanced Transportation*, *2021*(NA), 1-18. https://doi.org/10.1155/2021/8878011

[3] Al-Arafat, M., Kabi, M. E., Morshed, A. S. M., & Sunny, M. A. U. (2024). Geotechnical Challenges In Urban Expansion: Addressing Soft Soil, Groundwater, And Subsurface Infrastructure Risks In Mega Cities. *Innovatech Engineering Journal*, *1*(01), 205-222. https://doi.org/10.70937/itej.v1i01.20

[4] Al-Turjman, F. (2019). Cognitive routing protocol for disaster-inspired Internet of Things. *Future Generation Computer Systems*, *92*(NA), 1103-1115. https://doi.org/10.1016/j.future.2017.03.014

[5] Alam, M. A., Sohel, A., Hasan, K. M., & Ahmad, I. (2024). Advancing Brain Tumor Detection Using Machine Learning And Artificial Intelligence: A Systematic Literature Review Of Predictive Models And Diagnostic Accuracy. *Strategic Data Management and Innovation*, *1*(01), 37-55. https://doi.org/10.71292/sdmi.v1i01.6

[6] Alam, M. J., Rappenglueck, B., Retama, A., & Rivera-Hernández, O. (2024). Investigating the Complexities of VOC Sources in Mexico City in the Years 2016–2022. *Atmosphere*, *15*(2).

[7] AlHinai, Y. S. (2020). Disaster Management Digitally Transformed: Exploring the Impact and Key Determinants from the UK National Disaster Management Experience. *International journal of disaster risk reduction : IJDRR*, *51*(NA), 101851-101851. https://doi.org/10.1016/j.ijdrr.2020.101851

[8] Almatared, M., Liu, H., Abudayyeh, O., Hakim, O., & Sulaiman, M. (2023). Digital-Twin-Based Fire Safety Management Framework for Smart Buildings. *Buildings*, *14*(1), 4-4. https://doi.org/10.3390/buildings14010004

[9] Alomari, M. K., Khan, H. U., Khan, S., Al-Maadid, A. A., Abu-Shawish, Z. K., & Hammami, H. (2021). Systematic Analysis of Artificial Intelligence-Based Platforms for Identifying Governance and Access Control. *Security and Communication Networks*, *2021*(NA), 1-10. https://doi.org/10.1155/2021/8686469

[10] Alsarhan, A., Al-Dubai, A., Min, G., Zomaya, A. Y., & Bsoul, M. (2018). A New Spectrum Management Scheme for Road Safety in Smart Cities. *IEEE Transactions on Intelligent Transportation Systems*, *19*(11), 3496-3506. https://doi.org/10.1109/tits.2017.2784548

[11] Arafat, K. A. A., Bhuiyan, S. M. Y., Mahamud, R., & Parvez, I. (2024, 30 May-1 June 2024). Investigating the Performance of Different Machine Learning Models for Forecasting Li-ion Battery Core Temperature Under Dynamic Loading Conditions. 2024 IEEE International Conference on Electro Information Technology (eIT),

[12] Beg, A., Qureshi, A. R., Sheltami, T. R., & Yasar, A. (2020). UAV-enabled intelligent traffic policing and emergency response handling system for the smart city. *Personal and Ubiquitous Computing*, *25*(1), 33-50. https://doi.org/10.1007/s00779-019-01297-y

[13] Bhuiyan, S. M. Y., Mostafa, T., Schoen, M. P., & Mahamud, R. (2024). Assessment of Machine Learning Approaches for the Predictive Modeling of Plasma-Assisted Ignition Kernel Growth. ASME 2024 International Mechanical Engineering Congress and Exposition,

[14] Bieder, C. (2018). Societal Risk Communication—Towards Smart Risk Governance and Safety Management. In (Vol. NA, pp. 155-175). Springer International Publishing. https://doi.org/10.1007/978-3-319-74098-0_11

[15] Bonci, A., Carbonari, A., Cucchiarelli, A., Messi, L., Pirani, M., & Vaccarini, M. (2019). A cyber-physical system approach for building efficiency monitoring. *Automation in Construction*, *102*(NA), 68-85. https://doi.org/10.1016/j.autcon.2019.02.010

[16] Bonilla, S. H., Silva, H. R. O., da Silva, M. T., Gonçalves, R. F., & Sacomano, J. B. (2018). Industry 4.0 and Sustainability Implications: A Scenario-Based Analysis of the Impacts and Challenges. *Sustainability*, *10*(10), 3740-NA. https://doi.org/10.3390/su10103740

[17] Bosher, L. S., Dainty, A. R. J., Carrillo, P. M., Glass, J., & Price, A. D. F. (2007). Integrating disaster risk management into construction: A UK perspective. *Building Research & Information*, *35*(2), 163-177. https://doi.org/10.1080/09613210600979848

[18] Caprotti, F., & Cowley, R. (2019). Varieties of smart urbanism in the UK: Discursive logics, the state and local urban context. *Transactions of the Institute of British Geographers*, *44*(3), 587-601. https://doi.org/10.1111/tran.12284

[19] Chen, N., Liu, W., Bai, R.-z., & Chen, A. (2017). Application of computational intelligence technologies in emergency management: a literature review. *Artificial Intelligence Review*, *52*(3), 2131-2168. https://doi.org/10.1007/s10462-017-9589-8

[20] Choi, J., Ghannad, P., & Lee, Y.-C. (2020). Feasibility and Implications of the Modular Construction Approach for Rapid Post-Disaster Recovery. *International Journal of Industrialized Construction*, *1*(1), 64-75. https://doi.org/10.29173/ijic220

[21] Ćosić, K., Popović, S., & Wiederhold, B. K. (2024). Enhancing Aviation Safety through AI-Driven Mental Health Management for Pilots and Air Traffic Controllers. *Cyberpsychology, behavior and social networking*, *27*(8), 588-598. https://doi.org/10.1089/cyber.2023.0737

[22] Dasgupta, A., & Islam, M. M., Nahid, Omar Faruq, Rahmatullah, Rafio, . (2024). Engineering Management Perspectives on Safety Culture in Chemical and Petrochemical Plants: A Systematic Review. *ACADEMIC JOURNAL ON SCIENCE, TECHNOLOGY, ENGINEERING & MATHEMATICS EDUCATION*, *1*(1), 10.69593.

[23] Dick, K., Russell, L., Dosso, Y. S., Kwamena, F., & Green, J. R. (2019). Deep Learning for Critical Infrastructure Resilience. *Journal of Infrastructure Systems*, *25*(2), 05019003-NA. https://doi.org/10.1061/(asce)is.1943-555x.0000477

[24] Eswaraprasad, R., & Raja, L. (2017). Improved intelligent transport system for reliable traffic control management by adapting internet of things. *2017 International Conference on Infocom Technologies and Unmanned Systems (Trends and Future Directions) (ICTUS)*, *NA*(NA), 597-601. https://doi.org/10.1109/ictus.2017.8286079

[25] Evgrafova, I., Egorova, L., Marchenko, A., & Tarasov, A. (2022). Ethical problems of practical interaction between strong artificial intelligence and humans in the urban transport environment and legal proceedings. *Transportation Research Procedia*, *63*(NA), 2094-2098. https://doi.org/10.1016/j.trpro.2022.06.234

[26] Fang, Q., Castro-Lacouture, D., & Li, C. (2024). Smart Safety: Big Data–Enabled System for Analysis and Management of Unsafe Behavior by Construction Workers. *Journal of Management in Engineering*, *40*(1), NA-NA. https://doi.org/10.1061/jmenea.meeng-5498

[27] Fatemidokht, H., Rafsanjani, M. K., Gupta, B. B., & Hsu, C.-H. (2021). Efficient and Secure Routing Protocol Based on Artificial Intelligence Algorithms With UAV-Assisted for Vehicular Ad Hoc Networks in Intelligent Transportation Systems. *IEEE Transactions on Intelligent Transportation Systems*, *22*(7), 4757-4769. https://doi.org/10.1109/tits.2020.3041746

[28] Fernando, R. L. S. (2020). Artificial Intelligence and Disaster Management in Sri Lanka: Problems and Prospects. In (Vol. NA, pp. 149-166). Springer Nature Singapore. https://doi.org/10.1007/978-981-15-4291-6_11

[29] Gamil, Y., Abdullah, M. A., Rahman, I. A. R., & Asad, M. M. (2020). Internet of things in construction industry revolution 4.0: Recent trends and challenges in the Malaysian context. *Journal of Engineering, Design and Technology*, *18*(5), 1091-1102. https://doi.org/10.1108/jedt-06-2019-0164

[30] Garza-Reyes, J. A. (2015). Lean and green – a systematic review of the state of the art literature. *Journal of Cleaner Production*, *102*(NA), 18-29. https://doi.org/10.1016/j.jclepro.2015.04.064

[31] Gautami, A., & Gowthaman, N. (2021). A Holistic Approach: Issues and Challengesin Autonomic Computation Toward Industry 4.0. In (Vol. NA, pp. 111-121). Springer International Publishing. https://doi.org/10.1007/978-3-030-71756-8_6

[32] Getuli, V., Capone, P., Bruttini, A., & Sorbi, T. (2021). A smart objects library for BIM-based construction site and emergency management to support mobile VR safety training experiences. *Construction Innovation*, *22*(3), 504-530. https://doi.org/10.1108/ci-04-2021-0062

[33] Ghaffarian, S., Kerle, N., & Filatova, T. (2018). Remote Sensing-Based Proxies for Urban Disaster Risk Management and Resilience: A Review. *Remote Sensing*, *10*(11), 1760-NA. https://doi.org/10.3390/rs10111760

[34] Green, A. W., Woszczynski, A. B., Dodson, K., & Easton, P. (2020). Responding to Cybersecurity Challenges: Securing Vulnerable U.S. Emergency Alert Systems. *Communications of the Association for Information Systems*, *46*(1), 187-208. https://doi.org/10.17705/1cais.04608

[35] Gura, D. A., Dubenko, Y. V., Shevchenko, G. G., Dyshkant, E. E., & Khusht, N. I. (2020). Three-Dimensional Laser Scanning for Safety of Transport Infrastructure with Application of Neural Network Algorithms and Methods of Artificial Intelligence. In (Vol. NA, pp. 185-190). Springer Singapore. https://doi.org/10.1007/978-981-15-0454-9_19

[36] Ho, H. J., Zhang, Z. X., Huang, Z., Aung, A. H., Lim, W.-Y., & Chow, A. (2020). Use of a Real-Time Locating System for Contact Tracing of Health Care Workers During the COVID-19 Pandemic at an Infectious Disease Center in Singapore: Validation Study. *Journal of medical Internet research*, *22*(5), e19437-NA. https://doi.org/10.2196/19437

[37] Hossain, A., Khan, M. R., Islam, M. T., & Islam, K. S. (2024). Analyzing The Impact Of Combining Lean Six Sigma Methodologies With Sustainability Goals. *Journal of Science and Engineering Research*, *1*(01), 123-144. https://doi.org/10.70008/jeser.v1i01.57

[38] Hossain, M. R., Mahabub, S., & Das, B. C. (2024). The role of AI and data integration in enhancing data protection in US digital public health an empirical study. *Edelweiss Applied Science and Technology*, *8*(6), 8308-8321.

[39] Huang, X., Wang, B., & Wu, C. (2022). Realizing Smart Safety Management in the Era of Safety 4.0: A New Method towards Sustainable Safety. *Sustainability*, *14*(21), 13915-13915. https://doi.org/10.3390/su142113915

[40] Inderwildi, O. R., Zhang, C., Wang, X., & Kraft, M. (2020). The impact of intelligent cyber-physical systems on the decarbonization of energy. *Energy & Environmental Science*, *13*(3), 744-771. https://doi.org/10.1039/c9ee01919g

[41] Iordache, V., Gheroghiu, R. A., Stan, V. A., & Tarla, M. (2019). ZigBee localization system for public transport vehicles. *2019 11th International Conference on Electronics, Computers and Artificial Intelligence (ECAI)*, *NA*(NA), 1-4. https://doi.org/10.1109/ecai46879.2019.9042022

[42] Islam, M. M., Prodhan, R. K., Shohel, M. S. H., & Morshed, A. S. M. (2025). Robotics and Automation in Construction Management Review Focus: The application of robotics and automation technologies in construction. *Journal of Next-Gen Engineering Systems*, *2*(01), 48-71. https://doi.org/10.70937/jnes.v2i01.63

[43] Islam, M. M., Shofiullah, S., Sumi, S. S., & Shamim, C. M. A. H. (2024). Optimizing HVAC Efficiency And Reliability: A Review Of Management Strategies For Commercial And Industrial Buildings. *ACADEMIC JOURNAL ON SCIENCE, TECHNOLOGY, ENGINEERING & MATHEMATICS EDUCATION*, *4*(04), 74-89. https://doi.org/10.69593/ajsteme.v4i04.129

[44] Islam, M. T. (2024). A Systematic Literature Review On Building Resilient Supply Chains Through Circular Economy And Digital Twin Integration. *Frontiers in Applied Engineering and Technology*, *1*(01), 304-324. https://doi.org/10.70937/faet.v1i01.44

[45] Islam, M. T., Islam, K. S., Hossain, A., & Khan, M. R. (2025). Reducing Operational Costs in U.S. Hospitals Through Lean Healthcare And Simulation-Driven Process Optimization. *Journal of Next-Gen Engineering Systems*, *2*(01), 11-28. https://doi.org/10.70937/jnes.v2i01.50

[46] Jahan, F. (2024). A Systematic Review Of Blue Carbon Potential in Coastal Marshlands: Opportunities For Climate Change Mitigation And Ecosystem Resilience. *Frontiers in Applied Engineering and Technology*, *2*(01), 40-57. https://doi.org/10.70937/faet.v2i01.52

[47] Jiang, W., Ding, L., & Zhou, C. (2020). Cyber physical system for safety management in smart construction site. *Engineering, Construction and Architectural Management*, *28*(3), 788-808. https://doi.org/10.1108/ecam-10-2019-0578

[48] Jim, M. M. I., Hasan, M., & Munira, M. S. K. (2024). The Role Of AI In Strengthening Data Privacy For Cloud Banking. *Frontiers in Applied Engineering and Technology*, *1*(01), 252-268. https://doi.org/10.70937/faet.v1i01.39

[49] Joshi, S., Saxena, S., Godbole, T., & Shreya, N. A. (2016). Developing Smart Cities: An Integrated Framework. *Procedia Computer Science*, *93*(NA), 902-909. https://doi.org/10.1016/j.procs.2016.07.258

[50] Kagermann, H., & Wahlster, W. (2022). Ten Years of Industrie 4.0. *Sci*, *4*(3), 26-26. https://doi.org/10.3390/sci4030026

[51] Kaul, A., & Altaf, I. (2022). Vanet‐TSMA: A traffic safety management approach for smart road transportation in vehicular ad hoc networks. *International Journal of Communication Systems*, *35*(9), NA-NA. https://doi.org/10.1002/dac.5132

[52] Khan, H. U., Alomari, M. K., Khan, S., Nazir, S., Gill, A. Q., Al-Maadid, A., Abu-Shawish, Z. K., & Hassan, M. K. (2021). Systematic Analysis of Safety and Security Risks in Smart Homes. *Computers, Materials & Continua*, *68*(1), 1409-1428. https://doi.org/10.32604/cmc.2021.016058

[53] Khan, H. U., Malik, M. Z., Alomari, M. K. B., Khan, S., Al-Maadid, A. A. S. A., Hassan, M. K., & Khan, K. (2022). Transforming the Capabilities of Artificial Intelligence in GCC Financial Sector: A Systematic Literature Review. *Wireless Communications and Mobile Computing*, *2022*(NA), 1-17. https://doi.org/10.1155/2022/8725767

[54] Khan, S., Khan, S., Ali, Y., Khalid, M., Ullah, Z., & Mumtaz, S. (2022). Highly Accurate and Reliable Wireless Network Slicing in 5th Generation Networks: A Hybrid Deep Learning Approach. *Journal of Network and Systems Management*, *30*(2), NA-NA. https://doi.org/10.1007/s10922-021-09636-2

[55] Khan, Z. F., & Alotaibi, R. (2020). Applications of Artificial Intelligence and Big Data Analytics in m-Health: A Healthcare System Perspective. *Journal of healthcare engineering*, *2020*(NA), 8894694-8894615. https://doi.org/10.1155/2020/8894694

[56] Kong, L., & Woods, O. (2018). The ideological alignment of smart urbanism in Singapore: Critical reflections on a political paradox. *Urban Studies*, *55*(4), 679-701. https://doi.org/10.1177/0042098017746528

[57] Król, A. (2016). The Application of the Artificial Intelligence Methods for Planning of the Development of the Transportation Network. *Transportation Research Procedia*, *14*(NA), 4532-4541. https://doi.org/10.1016/j.trpro.2016.05.376

[58] Ku, J.-H., & Park, D.-K. (2013). Developing Safety Management Systems for Track Workers Using Smart Phone GPS. *International Journal of Control and Automation*, *6*(5), 137-148. https://doi.org/10.14257/ijca.2013.6.5.13

[59] Kumar, A., Rajalakshmi, K., Jain, S., Nayyar, A., & Abouhawwash, M. (2020). A novel heuristic simulation‐optimization method for critical infrastructure in smart transportation systems. *International Journal of Communication Systems*, *33*(11), NA-NA. https://doi.org/10.1002/dac.4397

[60] Lee, E. A. (2008). ISORC - Cyber Physical Systems: Design Challenges. *2008 11th IEEE International Symposium on Object and Component-Oriented Real-Time Distributed Computing (ISORC)*, *NA*(NA), 363-369. https://doi.org/10.1109/isorc.2008.25

[61] Lee, J., Bagheri, B., & Kao, H.-A. (2015). A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems. *Manufacturing Letters*, *3*(NA), 18-23. https://doi.org/10.1016/j.mfglet.2014.12.001

[62] Lei, Y., Rao, Y., Wu, J., & Lin, C.-H. (2020). BIM based cyber-physical systems for intelligent disaster prevention. *Journal of Industrial Information Integration*, *20*(NA), 100171-NA. https://doi.org/10.1016/j.jii.2020.100171

[63] Leszczynski, A. (2016). Speculative futures: Cities, data, and governance beyond smart urbanism. *Environment and Planning A: Economy and Space*, *48*(9), 1691-1708. https://doi.org/10.1177/0308518x16651445

[64] Li, G., Wang, J., & Wang, X. (2023). Construction and Path of Urban Public Safety Governance and Crisis Management Optimization Model Integrating Artificial Intelligence Technology. *Sustainability*, *15*(9), 7487-7487. https://doi.org/10.3390/su15097487

[65] Liu, Y., Yu, L., Chi, T., Yang, B., Yao, X., Yang, L., Zhang, X., Ren, Y., Liu, S., Cui, S., & Peng, L. (2017). Design and implementation of community safety management oriented public information platform for a smart city. *2017 Forum on Cooperative Positioning and Service (CPGPS)*, *NA*(NA), 330-332. https://doi.org/10.1109/cpgps.2017.8075149

[66] Mahabub, S., Das, B. C., & Hossain, M. R. (2024). Advancing healthcare transformation: AI-driven precision medicine and scalable innovations through data analytics. *Edelweiss Applied Science and Technology*, *8*(6), 8322-8332.

[67] Mahabub, S., Jahan, I., Hasan, M. N., Islam, M. S., Akter, L., Musfiqur, M., Foysal, R., & Onik, M. K. R. (2024). Efficient detection of tomato leaf diseases using optimized Compact Convolutional Transformers (CCT) Model.

[68] Mahabub, S., Jahan, I., Islam, M. N., & Das, B. C. (2024). The Impact of Wearable Technology on Health Monitoring: A Data-Driven Analysis with Real-World Case Studies and Innovations. *Journal of Electrical Systems*, *20*.

[69] Mahdy, I. H., Roy, P. P., & Sunny, M. A. U. (2023). Economic Optimization of Bio-Crude Isolation from Faecal Sludge Derivatives. *European Journal of Advances in Engineering and Technology*, *10*(10), 119-129.

[70] Malik, M. Z., Khan, S., & Khan, H. U. (2022). Transforming the competencies of Artificial Intelligence to ensure the Cyber Threats: A Systemic Literture Review of Busniess Sectors. *2022 1st International Conference on AI in Cybersecurity (ICAIC)*, *3*(NA), 1-6. https://doi.org/10.1109/icaic53980.2022.9897051

[71] Malik, M. Z., Nazir, S., & Khan, H. U. (2023). Artificial Intelligence Based System on Enhancing the Capabilities of Transport System: A Systemic Literature Review. *2023 IEEE Symposium on Industrial Electronics & Applications (ISIEA)*, *33*, 1-6. https://doi.org/10.1109/isiea58478.2023.10212340

[72] Miles, J. C., & Walker, A. J. (2006). The potential application of artificial intelligence in transport. *IEE Proceedings - Intelligent Transport Systems*, *153*(3), 183-198. https://doi.org/10.1049/ip-its:20060014

[73] Mohebbi, S., Zhang, Q., Wells, E. C., Zhao, T., Nguyen, H., Li, M., Abdel-Mottaleb, N., Uddin, S., Lu, Q., Wakhungu, M. J., Wu, Z., Zhang, Y., Tuladhar, A., & Ou, X. (2020). Cyber-physical-social interdependencies and organizational resilience: A review of water, transportation, and cyber infrastructure systems and processes. *Sustainable Cities and Society*, *62*(NA), 102327-NA. https://doi.org/10.1016/j.scs.2020.102327

[74] Mridha Younus, S. H., amp, & Md Morshedul, I. (2024). ADVANCED BUSINESS ANALYTICS IN TEXTILE & FASHION INDUSTRIES: DRIVING INNOVATION AND SUSTAINABLE GROWTH. *International Journal of Management Information Systems and Data Science*, *1*(2), 37-47. https://doi.org/10.62304/ijmisds.v1i2.143

[75] Mridha Younus, S. H. P. M. R. A. I. T., amp, & Rajae, O. (2024). SUSTAINABLE FASHION ANALYTICS: PREDICTING THE FUTURE OF ECO-FRIENDLY TEXTILE. *Global Mainstream Journal of Business, Economics, Development & Project Management*, *3*(03), 13-26. https://doi.org/10.62304/jbedpm.v3i03.85

[76] Munira, M. S. K. (2025). Digital Transformation in Banking: A Systematic Review Of Trends, Technologies, And Challenges. *Strategic Data Management and Innovation*, *2*(01), 78-95. https://doi.org/10.71292/sdmi.v2i01.12

[77] Murphy, R. R. (2014). *Disaster Robotics* (Vol. NA). The MIT Press. https://doi.org/10.7551/mitpress/9407.001.0001

[78] Nazir, S., Khan, S., Khan, H. U., Ali, S., García-Magariño, I., Atan, R., & Nawaz, M. (2020). A Comprehensive Analysis of Healthcare Big Data Management, Analytics and Scientific Programming. *IEEE Access*, *8*(NA), 95714-95733. https://doi.org/10.1109/access.2020.2995572

[79] Nguyen, W. P. V., & Nof, S. Y. (2019). Collaborative response to disruption propagation (CRDP) in cyber-physical systems and complex networks. *Decision Support Systems*, *117*(NA), 1-13. https://doi.org/10.1016/j.dss.2018.11.005

[80] O'Donovan, P., Leahy, K., Bruton, K., & O'Sullivan, D. T. J. (2015). Big data in manufacturing: a systematic mapping study. *Journal of Big Data*, *2*(1), 20-NA. https://doi.org/10.1186/s40537-015-0028-x

[81] Okrepilov, V. V., Kovalenko, B. B., Getmanova, G. V., & Turovskaj, M. S. (2022). Modern Trends in Artificial Intelligence in the Transport System. *Transportation Research Procedia*, *61*(NA), 229-233. https://doi.org/10.1016/j.trpro.2022.01.038

[82] Olugbade, S., Ojo, S., Imoize, A. L., Isabona, J., & Alaba, M. O. (2022). A Review of Artificial Intelligence and Machine Learning for Incident Detectors in Road Transport Systems. *Mathematical and Computational Applications*, *27*(5), 77-77. https://doi.org/10.3390/mca27050077

[83] Park, S., Lee, S., Jang, H., Yoon, G., Choi, M.-i., Kang, B., Cho, K., Lee, T., & Park, S. (2023). Smart Fire Safety Management System (SFSMS) Connected with Energy Management for Sustainable Service in Smart Building Infrastructures. *Buildings*, *13*(12), 3018-3018. https://doi.org/10.3390/buildings13123018

[84] Pollio, A. (2016). Technologies of austerity urbanism: the "smart city" agenda in Italy (2011–2013). *Urban Geography*, *37*(4), 514-534. https://doi.org/10.1080/02723638.2015.1118991

[85] Qiang, X., Huiqi, Z., Ali, F., & Nazir, S. (2021). Criterial Based Opinion Leader's Selection for Decision-Making Using Ant Colony Optimization. *Scientific Programming*, *2021*(NA), 1-12. https://doi.org/10.1155/2021/4624334

[86] Rad, M. H., Mojtahedi, M., & Ostwald, M. J. (2021). Industry 4.0, Disaster Risk Management and Infrastructure Resilience: A Systematic Review and Bibliometric Analysis. *Buildings*, *11*(9), 411. https://doi.org/10.3390/buildings11090411

[87] Rahaman, T., & Islam, M. S. (2021). Study of shrinkage of concrete using normal weight and lightweight aggregate. *International Journal of Engineering Applied Sciences and Technology*, *6*(6), 0-45.

[88] Rahaman, T., Siddikui, A., Abid, A.-A., & Ahmed, Z. (2024). Exploring the Viability of Circular Economy in Wastewater Treatment Plants: Energy Recovery and Resource Reclamation. *Well Testing*, *33*(S2).

[89] Rana, M. R. I., Jestratijevic, I. M., Rahman, M. M., & Siddiqi, M. T. H. (2024). Investigating Modern Slavery in the Post-Pandemic Textile and Apparel Supply Chain: An Exploratory Study. International Textile and Apparel Association Annual Conference Proceedings,

[90] Roy, P. P., Abdullah, M. S., & Sunny, M. A. U. (2024). Revolutionizing Structural Engineering: Innovations in Sustainable Design and Construction. *European Journal of Advances in Engineering and Technology*, *11*(5), 94-99.

[91] Rudskoy, A. I., Ilin, I., & Prokhorov, A. (2021). Digital Twins in the Intelligent Transport Systems. *Transportation Research Procedia*, *54*(NA), 927-935. https://doi.org/10.1016/j.trpro.2021.02.152

[92] Ruiying, L., Xiaoyu, T., Li, Y., & Rui, K. (2019). A Systematic Disturbance Analysis Method for Resilience Evaluation: A Case Study in Material Handling Systems. *Sustainability*, *11*(5), 1447-NA. https://doi.org/10.3390/su11051447

[93] Sabid, A. M., & Kamrul, H. M. (2024). Computational And Theoretical Analysis On The Single Proton Transfer Process In Adenine Base By Using DFT Theory And Thermodynamics. *IOSR Journal of Applied Chemistry*.

[94] Sarkar, M., Rashid, M. H. O., Hoque, M. R., & Mahmud, M. R. (2025). Explainable AI In E-Commerce: Enhancing Trust And Transparency In AI-Driven Decisions. *Innovatech Engineering Journal*, *2*(01), 12-39. https://doi.org/10.70937/itej.v2i01.53

[95] Sarker, I. H., Furhad, H., & Nowrozy, R. (2021). AI-Driven Cybersecurity: An Overview, Security Intelligence Modeling and Research Directions. *SN Computer Science*, *2*(3), 1-18. https://doi.org/10.1007/s42979-021-00557-0

[96] Shimul, A. I., Haque, M. M., Ghosh, A., Sunny, M. A. U., Aljazzar, S. O., Al-Humaidi, J. Y., & Mukhrish, Y. E. (2025). Hydrostatic Pressure-Driven Insights into Structural, Electronic, Optical, and Mechanical Properties of A3PCl3 (A = Sr, Ba) Cubic Perovskites for Advanced Solar Cell Applications. *Journal of Inorganic and Organometallic Polymers and Materials*. https://doi.org/10.1007/s10904-025-03629-3

[97] Shorfuzzaman, M., Hossain, M. S., & Alhamid, M. F. (2020). Towards the sustainable development of smart cities through mass video surveillance: A response to the COVID-19 pandemic. *Sustainable Cities and Society*, *64*(NA), 102582-102582. https://doi.org/10.1016/j.scs.2020.102582

[98] Siddiki, A., Al-Arafat, M., Arif, I., & Islam, M. R. (2024). Prisma Guided Review Of Ai Driven Automated Control Systems For Real Time Air Quality Monitoring In Smart Cities. *Journal of Machine Learning, Data Engineering and Data Science*, *1*(01), 147-162. https://doi.org/10.70008/jmldeds.v1i01.51

[99] Smigiel, C. (2018). Urban political strategies in times of crisis: A multiscalar perspective on smart cities in Italy. *European Urban and Regional Studies*, *26*(4), 336-348. https://doi.org/10.1177/0969776418792049

[100] Song, Y., Wang, X., Tan, Y., Wu, P., Sutrisna, M., Cheng, J. C. P., & Hampson, K. D. (2017). Trends and Opportunities of BIM-GIS Integration in the Architecture, Engineering and Construction Industry: A Review from a Spatio-Temporal Statistical Perspective. *ISPRS International Journal of Geo-Information*, *6*(12), 397-NA. https://doi.org/10.3390/ijgi6120397

[101] Sun, Y., Wang, X., & Tang, X. (2013). ICCV - Hybrid Deep Learning for Face Verification. *2013 IEEE International Conference on Computer Vision*, *NA*(NA), 1489-1496. https://doi.org/10.1109/iccv.2013.188

[102] Sunny, M. A. U. (2024a). Eco-Friendly Approach: Affordable Bio-Crude Isolation from Faecal Sludge Liquefied Product. *Journal of Scientific and Engineering Research*, *11*(5), 18-25.

[103] Sunny, M. A. U. (2024b). Effects of Recycled Aggregate on the Mechanical Properties and Durability of Concrete: A Comparative Study. *Journal of Civil and Construction Engineering*, 7-14.

[104] Sunny, M. A. U. (2024c). Unveiling spatial insights: navigating the parameters of dynamic Geographic Information Systems (GIS) analysis. *International Journal of Science and Research Archive*, *11*(2), 1976-1985.

[105] Thomas, J., & Harden, A. (2008). Methods for the thematic synthesis of qualitative research in systematic reviews. *BMC medical research methodology*, *8*(1), 45-45. https://doi.org/10.1186/1471-2288-8-45

[106] Tong, W., Hussain, A., Bo, W. X., & Maharjan, S. (2019). Artificial Intelligence for Vehicle-to-Everything: A Survey. *IEEE Access*, *7*(NA), 10823-10843. https://doi.org/10.1109/access.2019.2891073

[107] Tonoy, A. A. R. (2022). Mechanical Properties and Structural Stability of Semiconducting Electrides: Insights For Material. *Global Mainstream Journal of Innovation, Engineering & Emerging Technology*, *1*(01), 18-35. https://doi.org/10.62304/jieet.v1i01.225

[108] Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review. *British Journal of Management*, *14*(3), 207-222. https://doi.org/10.1111/1467-8551.00375

[109] Xiao, C., Chen, N., Gong, J., Wang, W., Hu, C., & Chen, Z. (2017). Event-Driven Distributed Information Resource-Focusing Service for Emergency Response in Smart City with Cyber-Physical Infrastructures. *ISPRS International Journal of Geo-Information*, *6*(8), 251-NA. https://doi.org/10.3390/ijgi6080251

[110] Yaacoub, J.-P. A., Noura, H. N., Salman, O., & Chehab, A. (2021). Robotics cyber security: vulnerabilities, attacks, countermeasures, and recommendations. *International journal of information security*, *21*(1), 1-44. https://doi.org/10.1007/s10207-021-00545-8

[111] Yao, F., & Wang, Y. (2020). Towards resilient and smart cities: A real-time urban analytical and geo-visual system for social media streaming data. *Sustainable Cities and Society*, *63*(NA), 102448-NA. https://doi.org/10.1016/j.scs.2020.102448

[112] Yigitcanlar, T., & Kamruzzaman, N. A. (2018). Smart cities and mobility: Does the smartness of Australian cities lead to sustainable commuting patterns? *Journal of Urban Technology*, *26*(2), 21-46. https://doi.org/10.1080/10630732.2018.1476794

[113] Younus, M. (2022). Reducing Carbon Emissions in The Fashion And Textile Industry Through Sustainable Practices and Recycling: A Path Towards A Circular, Low-Carbon Future. *Global Mainstream Journal of Business, Economics, Development & Project Management*, *1*(1), 57-76. https://doi.org/10.62304/jbedpm.v1i1.226

[114] Younus, M. (2025). The Economics of A Zero-Waste Fashion Industry: Strategies To Reduce Wastage, Minimize Clothing Costs, And Maximize & Sustainability. *Strategic Data Management and Innovation*, *2*(01), 116-137. https://doi.org/10.71292/sdmi.v2i01.15

[115] Zhang, Y. (2021). Safety Management of Civil Engineering Construction Based on Artificial Intelligence and Machine Vision Technology. *Advances in Civil Engineering*, *2021*(1), NA-NA. https://doi.org/10.1155/2021/3769634

[116] Zhao, C. (2021). Application of Virtual Reality and Artificial Intelligence Technology in Fitness Clubs. *Mathematical Problems in Engineering*, *2021*(NA), 1-11. https://doi.org/10.1155/2021/2446413