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Review Article

Artificial intelligence for drowning prevention: a scoping review for public health practice

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ABSTRACT

Drowning remains a major and preventable cause of injury mortality worldwide, with a disproportionate burden in low- and middle-income countries. Timely recognition of distress and rapid rescue can be missed within existing supervision systems. Artificial intelligence (AI) and machine learning (ML) technologies are increasingly proposed to strengthen drowning prevention through hazard prediction, real-time surveillance, wearable alerts, and drone-assisted response. We conducted a scoping review (2015–2023) of studies describing AI/ML applications for drowning prevention, detection, or rescue across electronic databases and selected grey literature. Evidence was synthesized by functional domain (hazard prediction, incident detection, rescue support) and conceptually mapped to the Haddon Matrix to examine potential contributions across pre-event, event, and post-event phases. Given heterogeneity in study designs and outcomes, findings were appraised descriptively with attention to validation context and implementation considerations. Thirty-eight studies met inclusion criteria. Most evaluated computer-vision systems in controlled pool or coastal environments, with fewer examining wearable sensors, drone-assisted localization, or environmental risk prediction. Reported performance metrics were frequently derived from simulation or prototype datasets, with limited independent field validation. Few studies assessed integration into lifeguard workflows, cost-effectiveness, or applicability in resource-limited settings. AI/ML technologies may complement established drowning prevention strategies by enhancing hazard surveillance and supporting rapid response. However, the current evidence base remains largely pre-implementation. Future research should prioritize real-world validation, transparent reporting, and evaluation of integration within injury prevention systems to determine whether these tools reduce drowning in practice.

Keywords: Drowning prevention, Artificial intelligence, Machine learning, Injury prevention, Global health, Low- and middle-income countries, Surveillance, Wearable devices, Drones

INTRODUCTION

Drowning is a leading and preventable cause of injury-related mortality worldwide. The Global Status Report on Drowning Prevention estimates approximately 300,000 drowning deaths annually, with the highest burden occurring in low- and middle-income countries.[1] The Global Burden of Disease 2017 study further demonstrates persistent regional disparities and substantial years of life lost due to unintentional drowning.[2] Even in high-income countries, drowning remains a significant public health concern, with variations in location, activity, and risk patterns complicating prevention strategies.[3]

Traditional prevention approaches such as swimming instruction, public education, environmental modification, and lifeguard supervision have contributed to risk reduction but face important limitations. Lifeguard systems are constrained by fatigue, visual obstruction, environmental complexity, and incomplete spatial coverage. Moreover, beachgoers frequently fail to identify hazardous conditions such as rip currents in real-world settings, despite educational efforts.[4] These challenges underscore the need for complementary strategies that enhance early hazard detection and rapid response. These functions align with core injury prevention priorities such as improving surveillance, strengthening supervision, and shortening time-to-rescue.

Advances in artificial intelligence (AI), machine learning (ML), and computer vision offer opportunities to augment conventional drowning prevention. Vision-based systems have demonstrated the ability to detect early drowning behaviors using overhead cameras and motion analysis.[5,6] Drone-assisted ML models have shown promising sensitivity and specificity in identifying simulated drowning victims in open water.[7] Additional approaches include wearable sensor systems and predictive models for environmental risk detection.

However, reported accuracy alone does not show whether these technologies will reduce drowning in real-world settings. For AI/ML tools to contribute to prevention, they must work reliably outside controlled environments, support lifeguards and emergency responders, remain feasible in low-resource settings, and follow appropriate ethical and safety standards. Although detection algorithms are improving, there is limited evidence on large-scale use, long-term performance, and integration into existing drowning prevention systems.

Using the Haddon Matrix framework, which organizes prevention into pre-event, event, and post-event phases, this scoping review summarizes current evidence on AI/ML applications in drowning prevention. The review examines where these technologies may fit within injury prevention practice and highlights gaps in validation, implementation, and public health relevance.

METHODS

This scoping review maps published evidence on AI/ML applications for drowning prevention, including wearables, mobile applications, drones, robotic systems, and video/surveillance systems. A comprehensive search was conducted across electronic databases, including PubMed, Scopus, IEEE Xplore, Web of Science, and Google Scholar, to identify relevant studies published between January 2015 and December 2023. Grey literature from sources, such as the World Health Organization (WHO), Centers for Disease Control and Prevention (CDC), and drowning prevention organizations (e.g., International Life Saving Federation), was also searched to capture non-peer-reviewed reports and practical implementations.

The search strategy combined specific keywords and Boolean operators to ensure comprehensive coverage of relevant literature. Search terms included: (“Artificial Intelligence” OR “Machine Learning” OR “Deep Learning” OR “Computer Vision”) AND (“Drowning Prevention” OR “Water Safety” OR “Drowning Detection”) AND (“Wearable Technology” OR “Wearable Devices” OR “Mobile Applications” OR “Drones” OR “Robotic Systems” OR “Surveillance Systems”). Filters were applied to limit results to English-language studies and publications from January 2015 to December 2023. Database-specific syntax was adapted (e.g., PubMed used Medical Subject Headings [MeSH] terms like “Drowning/prevention and control”), and truncation (e.g., drown*) was used to capture variations. Grey literature searches involved targeted queries on organizational websites and repositories (e.g., WHO Global Health Observatory) using similar terms. Citation tracking and reference list screening of included studies supplemented the search to identify additional relevant publications.

Studies were included if they (1) explicitly applied AI/ML techniques to drowning prevention, (2) examined prototype development, controlled testing, or field-based evaluation, (3) reported quantitative outcomes (e.g., accuracy, sensitivity, specificity, response time), and (4) were published between January 2015 and December 2023. Studies were excluded if they focused solely on non-drowning water safety issues (e.g., water quality) or lacked quantitative outcomes. Conference abstracts without sufficient methodological details, editorials, and non-English studies were also excluded to ensure robust data for analysis. Titles and abstracts were screened, followed by full-text review of potentially relevant records. Data were extracted into a standardized framework capturing the technology domain (wearables, mobile applications, drones, robotic systems, or video/surveillance), AI/ML technique, intended setting (pool, beach, river, or open water), evaluation approach (prototype, controlled testing, or field assessment), and key performance and implementation observations. Findings were synthesized narratively by technology category and mapped conceptually to the Haddon Matrix phases (pre-event, event, and post-event) to support a public-health interpretation of where AI/ML tools may contribute most effectively. Formal risk-of-bias scoring was not undertaken due to heterogeneity of study designs and outcomes. One reviewer screened titles/abstracts and full texts, and a second reviewer verified eligibility decisions for included studies.

Search results

The review followed structured scoping review principles, including systematic searching, predefined eligibility criteria, and transparent reporting of study selection. A total of 670 records were identified through database searches and other sources. After removal of 118 duplicates, 552 records were screened by title and abstract, of which 396 were excluded. 156 full-text articles were assessed for eligibility, and 118 were excluded for predefined reasons. Full-text exclusions were primarily due to lack of drowning-specific outcomes, absence of AI/ML methods, or insufficient evaluation detail. Thirty-eight studies met the inclusion criteria and were included in this scoping review.

OVERVIEW OF AI AND ML IN DROWNING DETECTION

AI and ML technologies are increasingly being applied in drowning prevention. These systems aim to support early hazard identification, real-time detection of distress, and rapid rescue response. ML models can analyze environmental and behavioural data to identify high-risk situations and assist authorities in planning preventive measures.

Sensors and cameras can be used in pools, beaches, and rivers to monitor water conditions and swimmer behaviour. Alert systems may notify lifeguards or emergency responders when abnormal patterns are detected. Drones may support rapid localization and delivery of flotation devices to improve response time. The process of ML in the detection of drowning is shown in Figure 1.

Table 2 summarizes selected AI/ML applications in drowning prevention, summarizing key findings, performance metrics, and their significance in enhancing water safety.

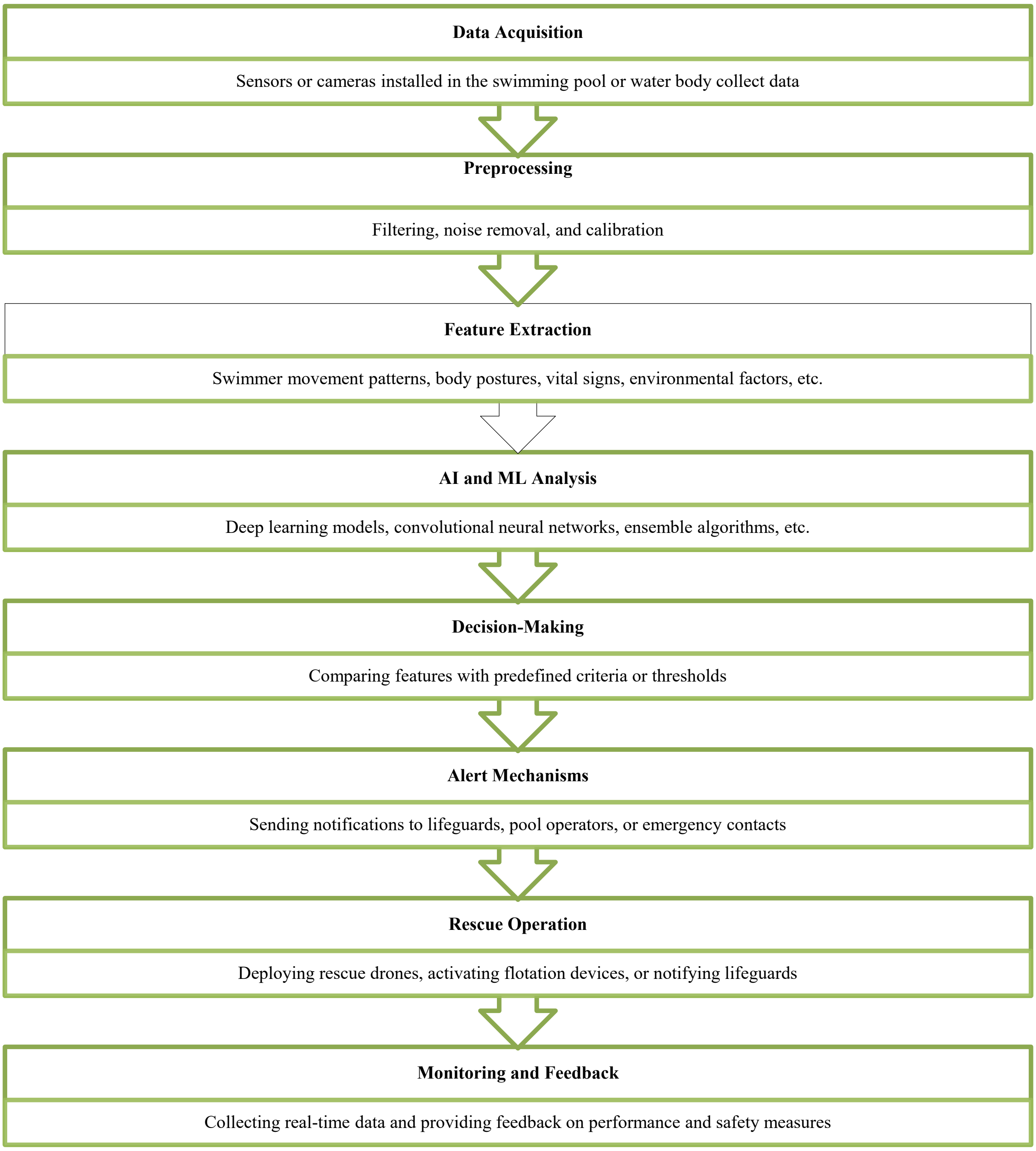

Figure 1: Process of machine learning in the detection of drowning.

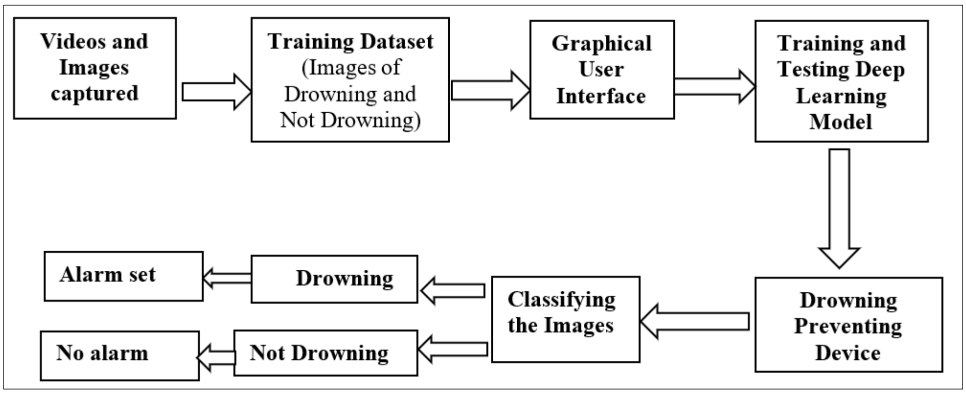

Figure 2: Deep learning technique in drowning detection.

TYPES OF EQUIPMENT TO RESCUE DROWNING VICTIMS

The AI and ML applications in drowning prevention are broadly categorized into the following.

Wearable device technologies

These devices use sensors to detect distress (e.g., motion, submersion, or vital signs) and trigger alerts. Wearable devices integrated with AI and ML can monitor individual swimmers, tracking their location, movement patterns, and vital signs. LifeTag activates when a person falls into water and transmits location and status information to nearby vessels, reporting high prediction accuracy in controlled testing.[8] Other systems detect loss of signal underwater and trigger alerts to rescuers.[9] Headband-based systems have also been developed to identify abnormal movement patterns in pools.[10] These devices aim to support faster rescue, although most evaluations have been conducted in prototype or controlled settings.

Mobile applications

Smartphone-based systems use built-in sensors to detect abnormal movement and send emergency alerts. One framework reported 98% accuracy in detecting falling or drowning events using sensor-based ML models.[11] Other systems monitor heart rate or water exposure and transmit alerts to caregivers or lifeguards.[12,13] The SOSeas web application uses environmental variables to generate beach risk flags and demonstrated accurate prediction of warning levels in Brazilian coastal settings.[14]

Drones

Drones equipped with computer-vision systems have been developed to identify individuals in distress and deliver rescue equipment. In a feasibility study, a drone-based ML model achieved 91% sensitivity and 90% specificity in detecting simulated drowning victims.[7] Other prototype systems have demonstrated automated victim localization and flotation delivery.[15,16] Some models use large, labeled image datasets to detect drowning behaviour and trigger alerts.[17] Most drone systems remain at prototype or pilot stages.

Robot system

Robotic systems have been proposed to support rescue in swimming pools. One system used overhead cameras to detect drowning and deploy a ring buoy automatically.18 Another system combined video surveillance with automated lifting mechanisms to assist victims.[19] These technologies are largely experimental, with limited evidence of real-world deployment.

Automatic waist airbag

Automatic flotation devices have also been developed. These systems use motion and pressure sensors to detect submersion and activate an airbag to assist the swimmer.[20,21] Evidence remains limited to prototype evaluations.

RIP CURRENT DETECTION AND LOCALIZATION

Rip currents are strong, reverse currents of water that pose a drowning risk to beachgoers. If the potential zones of rip currents are identified, coastal regions can be managed accordingly to prevent accidents. Visualizing rip currents increases perception and is associated with a higher intent to avoid them.[22] Rip current type classification is a resource to improve rip current education and awareness.[23] However, less than a quarter of beach-goers could identify in situ rip currents, and photographs did not help teach individuals to identify rip currents.[4] Rip current type classification is a resource to improve rip current education and awareness field.[24] However, less than a quarter of beachgoers could identify in situ rip currents, and photographs did not help teach individuals to identify rip currents.[25] AI-based image analysis has been used to detect and localize rip currents. CNN models such as VGG16 and DenseNet have reported high classification accuracy in beach and bathymetric images.[24] Interpretable AI methods have also been used to visualize rip current detection in video data.[25] The RipDet+ framework reported 98.6% accuracy in identifying rip currents.[26] Although performance appears promising, evidence of impact on drowning reduction remains limited.

INTEGRATION OF AI/ML WITHIN DROWNING PREVENTION SYSTEMS

AI/ML applications can be mapped onto the Haddon Matrix to clarify their potential role across pre-event, event, and post-event phases of drowning prevention. Pre-event tools may support hazard prediction and supervision planning; event-phase systems may assist in detecting distress and triggering alerts; and post-event technologies may support localization and rescue coordination (Table 1). However, these tools should complement, not replace, established drowning prevention strategies. Effective integration requires alignment with lifeguard systems, community education, and local safety policies. Lifeguards need training to interpret and respond to AI-generated alerts, and pilot testing in high-risk settings is essential before wider implementation. Programs should evaluate feasibility, reliability, cost, privacy considerations, and impact on response time. AI/ML systems are most likely to be effective when embedded within broader drowning prevention plans that include supervision, swimming education, and environmental safety measures. A schematic representation of the deep-learning approach used in drowning detection is shown in Figure 2.

Table 1: AI/ML applications in drowning prevention mapped to the Haddon matrix.

Phase	Host (swimmer)	Agent/vector (water/currents)	Environment (physical/social context)
Pre-event	Risk stratification based on swimming ability, behaviour, and exposure patterns	AI-based rip-current and hazard detection enabling preventive warnings or beach closures	Weather and crowd analytics guiding supervision planning and lifeguard allocation
Event	Wearable or smartphone-based detection of distress and abnormal movement	Computer-vision systems identifying struggling swimmers or hazardous flow patterns	Real-time surveillance and alert systems triggering rapid response
Post-event	Automated flotation delivery or assisted rescue support	Drone-based localisation and delivery of rescue equipment	Mobile-enabled emergency notification and post-incident evaluation

Table 2: Summary of AI/ML applications in drowning prevention: setting, evaluation approach, and reported performance.

Author	Technique	Description	Evaluation type	Setting	Sample size	Validation	Key findings
Cepeda-Pacheco and Domingo 2022[28]	Deep learning-based methods	Utilizes deep learning models to prevent child drowning incidents in swimming pool	Observational	Indoor pool	Not reported	Not reported	ResNet-50 detects caregiver distractions. Accuracy: 98%. Enhances caregiver supervision
Yu J[29]	Deep learning-based methods	American Red Cross' characteristics	Simulation	Swimming pool	Not reported	Not reported	CNN identifies drowning events from videos
He et al. 2022[30]	Deep learning-based methods	Real-time framework for infant drowning detection. Utilizes an attention-based YOLOv5-like model to filter out false detections and recognize	Simulation	Outdoor pool	7296 infant swimming images and 1222 test images	Train-test split (80:20)	Precision of 97.17% and processing speed of 43 frames per second when tested on videos from swimming pools

Continued.

Author	Technique	Description	Evaluation type	Setting	Sample size	Validation	Key findings
		swimming postures					
Chan et al. 2020[31]	Deep learning-based methods	Uses NVIDIA Jetson Nano in maritime visual surveillance for drowning prevention	Observational	Beach	Not reported	Not reported	Enhances maritime surveillance
Liu et al. 2023[32]	Computer vision techniques	Enables real-time underwater video analysis for body posture detection	Observational	Indoor pool	500 video clips	5-fold cross-validation	Overcomes scarcity of drowning video data
Shatnawi et al. 2023[33]	Computer vision techniques and deep learning	Utilises convolutional neural network models in early drowning detection	Observational	Beach	200 images	10-fold cross-validation	ResNet50 offers 100% prediction accuracy
Xie et al. 2022[34]	Ensemble algorithms to assess non-fatal drowning risk	Frequency of swimming, distance to open water, swimming skills, personality, family relations	Observational	River	8390 children	10-fold cross-validation	Stacking ensemble model predicts risk factors. AUC: 0.741; sensitivity: 0.625 in predicting non-fatal drowning
Shehata et al. 2021[35]	Surveillance systems	ML algorithms enhance real-time monitoring using image processing, accelerometer, and LASER techniques	Review	Indoor pool	Not reported	Not applicable	Track swimmers in pool and prevent drowning accidents
Laxman and Jain 2021[36]	Surveillance systems	IoT-based automation using sensors, programmable devices, and unique algorithms	Simulation	Indoor pool	Not reported	Not reported	Benefits various user groups like toddlers, inexperienced swimmers, and patients with seizures
Alshbatat et al. 2020[37]	Automated vision-based surveillance system	Uses Raspberry Pi, Pixy camera, and Arduino Nano board	Observational	Indoor pool	150 images	Not reported	Locates drowning swimmers and triggers alarm to alert lifeguards

Continued.

Author	Technique	Description	Evaluation type	Setting	Sample size	Validation	Key findings
Eng et al. 2003[6]	Surveillance systems using advanced segmentation algorithms	Accurately detects swimmers in challenging conditions by combining visual indicators and swimmer descriptors	Observational	Outdoor pool	300 video frames	Train-test split	Performs well in diverse environments and overcomes issues such as occlusions and lighting changes
Lu and Tan 2004[5]	Surveillance systems using vision-based approaches	Combines visual and event-inference components to detect and track swimmers. Utilizes finite state machines and motion-based reasoning	Observational	Indoor pool	200 video frames	Train-test split	Differentiates swimmers from background and detects drowning incidents in the swimming pool
Alotaibi 2020[38]	'ImageNet' for drowning detection	Leverages IoT and transfer learning and provides automated off-time monitoring of swimming pool by sending alerts to mobile device	Observational	Indoor pool	300 images	5-fold cross-validation	Differentiates between humans and objects with 99% classification accuracy
Yukta et al. 2022[39]	Real-time video-based surveillance systems	Uses a convolutional neural network object detector to detect human behaviour	Observational	Indoor pool	400 video frames	Train-test split	When difficulty is detected, the system triggers an alert to save a swimmer's life with an accuracy of 85%
Salehi et al. 2016[40]	Real-time video-based drowning detection	Colour space analysis and video sequence information to identify regions of interest. Triggers an alarm when a person is absent for a predetermined duration	Observational	Indoor pool	250 video clips	Not reported	Notifies lifeguard with minimal false alarms and a maximum delay of 2.6 seconds

Continued.

Author	Technique	Description	Evaluation type	Setting	Sample size	Validation	Key findings
Chavan et al. 2022[41]	Real-time video surveillance system	Cameras above pool automatically detect drownings	Observational	Indoor pool	500 images	5-fold cross-validation	Enhances pool safety
B David Prakash 2018[42]	Video-based surveillance system	The system (NEPTUNE) predicts near-drowning using short video sequences, statistical image processing, and K-means clustering	Observational	Indoor pool	300 video sequences	Train-test split	Integrated into a swimming pool camera system to alert lifeguards

CHALLENGES AND LIMITATIONS OF AI/ML IN DROWNING PREVENTION

Implementing AI/ML systems for drowning prevention presents several challenges. Data on drowning events and water conditions are often incomplete. Many models are developed using data from specific locations, which may limit their applicability in other settings, especially in LMIC river or rural environments. Infrastructure requirements such as reliable electricity, internet connectivity, and technical maintenance may restrict deployment in low-resource areas.

Surveillance tools such as cameras and drones raise privacy and ethical concerns. Clear governance and safety standards are required before large-scale implementation. While mobile applications and basic wearables may be relatively low-cost, drones and robotic systems require higher investment, training, and maintenance. These factors may limit scalability in resource-constrained settings. Although several studies report high accuracy, most evaluations were conducted in controlled or prototype environments. False-positive alerts may increase workload for lifeguards, while false negatives may miss critical events. Real-world conditions such as poor weather, water turbidity, and equipment limitations can reduce performance. Long-term field validation remains limited.

AI/ML systems may reflect biases in the datasets used for training. Many models are developed using data from high-income beach or pool settings. Their performance in riverine or rural LMIC contexts is largely unknown. Small sample sizes in some studies may also lead to overestimation of accuracy. Broader and more diverse datasets, along with independent field validation, are needed to improve generalizability and reliability. These limitations suggest that performance metrics should be interpreted as early-stage evidence rather than proof of public health impact.

CONCLUSION

This scoping review of thirty-eight studies suggests that AI/ML technologies may support drowning prevention by improving hazard identification, distress detection, and response coordination. When viewed through the Haddon Matrix, these tools have potential roles across pre-event, event, and post-event phases. However, most evidence comes from controlled or prototype settings, with limited real-world validation. Infrastructure constraints, cost, privacy concerns, and limited LMIC data remain important challenges. AI/ML systems should complement, not replace, established drowning prevention measures such as supervision, swimming education, and environmental safety strategies. Further field-based research is needed to determine their effectiveness and feasibility in routine practice.

Recommendations

AI/ML has potential to strengthen drowning prevention research. Large datasets may help identify risk patterns, high-risk locations, and gaps in supervision. Such evidence may support targeted prevention strategies and improve planning of resources. However, current research is concentrated in high-income countries. Evidence from LMIC settings remains limited despite the higher burden of drowning.

Many studies are based on small datasets or controlled environments, and few report long-term field validation. Future research should prioritize real-world evaluation in diverse settings, particularly in LMIC river and coastal environments. Multicentre studies and independent validation are needed to assess reliability, response time, and potential impact on drowning outcomes. Cost-effectiveness and integration with existing prevention systems should also be examined.

Pilot studies may be useful, but they should include clear outcome measures and sustainability assessments. Broader collaboration between public health researchers, local authorities, and technology developers will be important to ensure that AI/ML tools are safe, feasible, and context appropriate.

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