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Artificial Intelligence-Enhanced Clinical Decision Support Systems in Emergency Medical Services: A Framework for Implementation and Evaluation

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Abstract

This paper proposes a comprehensive framework for implementing and evaluating AI-enhanced clinical decision support systems (AI-CDSS) in EMS, addressing identified gaps in current research regarding real-time decision support, validation methodologies, and ethical considerations.A review of current literature on AI applications in prehospital care was conducted, identifying key research gaps, technological capabilities, and implementation challenges. The proposed framework integrates technical specifications, clinical workflows, validation protocols, and ethical safeguards.
The framework encompasses five core domains: (1) AI architecture and data integration, (2) clinical workflow integration, (3) validation and performance metrics, (4) ethical and legal considerations, and (5) continuous learning mechanisms. Key innovations include real-time multimodal data processing, explainable AI interfaces for paramedics, and prospective validation protocols.AI-CDSS represents a transformative opportunity for EMS, with potential to enhance diagnostic accuracy, reduce cognitive load, and improve patient outcomes. However, successful implementation requires rigorous prospective validation, attention to algorithmic bias, and preservation of clinical autonomy. Future research should prioritize field-based trials, diverse population validation, and long-term outcome studies.

Key Words: Emergency Medical Services, Artificial Intelligence, Clinical Decision Support, Prehospital Care, Machine Learning, Predictive Analytics

1. Introduction

1.1 Background

Emergency Medical Services (EMS) personnel function as the critical first link in the acute care continuum, making time-sensitive clinical decisions in uncontrolled environments with limited diagnostic resources. These prehospital providers must rapidly assess patients, initiate appropriate interventions, and determine optimal transport destinations—all while managing scene safety, equipment limitations, and environmental challenges (Basnawi, 2024). The complexity of this decision-making process, combined with increasing call volumes and workforce shortages, creates significant cognitive demands that can impact care quality and provider well-being.

Recent technological advances in artificial intelligence have demonstrated remarkable capabilities in medical diagnostics, prognostication, and clinical decision support within hospital settings. AI systems have shown proficiency in interpreting electrocardiograms, predicting sepsis onset, and optimizing resource allocation (Raff et al., 2024; Simpson et al., 2025). However, the translation of these technologies to prehospital environments presents unique challenges, including connectivity limitations, device portability, integration with existing workflows, and the need for split-second decision-making.

1.2 Research Gap

Current literature on AI in EMS has primarily focused on retrospective analyses of dispatch optimization, cardiac arrest prediction, and resource allocation (Mackenzie et al., 2023). A comprehensive scoping review by Goldberg et al. (2023) revealed that EMS-specific research has grown substantially, with publications increasing by 327% from 2001 to 2020. Despite this growth, significant gaps remain in understanding how AI can be effectively integrated into real-time clinical decision-making during active patient care.

Most existing studies employ internal validation with retrospective datasets, limiting generalizability to actual field conditions (Mackenzie et al., 2023). Furthermore, few frameworks exist to guide the systematic development, implementation, and evaluation of AI-CDSS specifically designed for the prehospital environment. This gap is particularly concerning given the unique constraints of EMS operations, including variable connectivity, diverse patient presentations, and the absence of comprehensive diagnostic equipment.

1.3 Research Objectives

This paper addresses these gaps by proposing a comprehensive framework for AI-enhanced clinical decision support in EMS. Specific objectives include:

1. Delineating technical requirements for AI-CDSS adapted to prehospital constraints
2. Developing integration protocols that preserve clinical workflow efficiency
3. Establishing rigorous validation methodologies appropriate for field conditions
4. Addressing ethical considerations specific to AI-assisted prehospital care
5. Proposing mechanisms for continuous system learning and improvement

2. Literature Review

2.1 Current State of AI in EMS

The integration of AI into EMS has evolved through several distinct applications. Early implementations focused on dispatch optimization and demand prediction, using machine learning algorithms to forecast call volumes and optimize unit positioning (Lawrence, 2024). These systems demonstrated significant improvements in response times and resource utilization but operated independently of clinical decision-making processes.

More recent developments have explored AI applications in clinical contexts, particularly cardiac arrest recognition and stroke identification. Copenhagen EMS, for example, has implemented AI-powered call analysis to detect cardiac events with high sensitivity, enabling earlier dispatcher-guided CPR instruction (Lawrence, 2024). These systems analyze caller speech patterns, background sounds, and response content to identify life-threatening conditions before EMS arrival.

Prognostic AI applications have shown particular promise. Studies have developed algorithms predicting outcomes for out-of-hospital cardiac arrest patients, achieving areas under the receiver operating characteristic curve (AUROC) exceeding 0.9 (Mackenzie et al., 2023). Neural networks and random forest models have been employed for triage support, risk stratification, and treatment outcome prediction. However, the majority of these applications remain research-focused, with limited deployment in operational settings.

2.2 Identified Research Gaps

Several critical gaps constrain current AI applications in EMS:

Validation Limitations: Most studies employ Type 1A or 1B internal validation using retrospective data, raising questions about real-world performance (Mackenzie et al., 2023). Few studies have conducted prospective external validation or tested systems under actual field conditions.

Integration Challenges: Limited research addresses the practical integration of AI tools into existing EMS workflows. Questions remain regarding device form factors, user interface design, and the cognitive impact of introducing AI recommendations during active patient care.

Ethical Frameworks: While concerns about algorithmic bias, liability, and clinical autonomy have been raised, comprehensive ethical frameworks specific to prehospital AI implementation remain underdeveloped (Ventura & Denton, 2023).

Explainability and Trust: The "black box" nature of many AI algorithms poses challenges for clinical adoption. EMS providers require transparent, explainable recommendations to maintain trust and appropriate clinical skepticism (Tozer, 2024).

2.3 Technological Capabilities

Current AI technologies offer several capabilities relevant to prehospital care:

Natural Language Processing (NLP): NLP can automate documentation, extract relevant information from patient history, and enable voice-controlled device operation—particularly valuable when providers' hands are occupied with patient care (Ventura & Denton, 2023).

Computer Vision: AI-powered image analysis can assist with interpretation of prehospital ultrasound, wound assessment, and even analysis of visual patient presentation patterns that may indicate specific conditions (Tozer, 2024).

Predictive Analytics: Machine learning models can analyze vital signs, patient history, and environmental factors to predict clinical deterioration, guide destination selection, and recommend intervention timing (Weidman et al., 2025).

Edge Computing: Advances in edge AI enable complex algorithms to run on portable devices without continuous connectivity, addressing a critical constraint in prehospital environments.

3. Proposed Framework for AI-CDSS in EMS

3.1 System Architecture

The proposed AI-CDSS framework consists of five integrated components designed to function within prehospital operational constraints:

3.1.1 Data Acquisition Layer

This foundational layer aggregates multimodal data from various sources:

- **Physiological monitoring:** Continuous vital signs from patient monitoring equipment (ECG, pulse oximetry, capnography, blood pressure)
- **Environmental sensors:** Ambient temperature, noise levels, scene characteristics
- **Historical data:** Patient medical history retrieved from regional health information exchanges
- **Provider input:** Voice-recorded assessment findings, physical examination observations
- **Visual data:** When available, images from point-of-care ultrasound or wound documentation

Critical to this layer is the implementation of standardized data formats and interoperability protocols ensuring seamless integration with existing equipment. Data acquisition must occur with minimal disruption to clinical workflow, prioritizing passive collection over manual data entry.

3.1.2 AI Processing Core

The central processing component employs multiple AI algorithms optimized for different decision support functions:

- **Diagnostic Support Models:** Neural networks trained on large datasets of prehospital patient presentations, capable of suggesting differential diagnoses based on presenting symptoms, vital signs, and examination findings
- **Risk Stratification Algorithms:** Machine learning models predicting likelihood of clinical deterioration, need for advanced interventions, or adverse outcomes
- **Treatment Recommendation Engines:** Systems providing evidence-based treatment suggestions adapted to available resources and provider certification level
- **Destination Selection Algorithms:** Models recommending optimal receiving facilities based on patient condition, facility capabilities, transport times, and receiving department capacity

The processing core is designed with modular architecture, allowing individual components to be updated independently as new evidence emerges or additional capabilities are developed.

3.1.3 Explainable Interface Layer

Recognition that EMS providers must understand and trust AI recommendations led to emphasis on explainable AI principles. The interface layer translates complex algorithmic outputs into clear, actionable guidance:

- **Confidence Indicators:** Transparent communication of recommendation certainty
- **Reasoning Transparency:** Brief explanations of key factors driving recommendations
- **Alternative Considerations:** Presentation of differential diagnoses or alternative approaches with associated probabilities
- **Human Override Mechanisms:** Clear pathways for providers to deviate from AI recommendations with documentation of clinical reasoning

Interface design prioritizes cognitive ergonomics, presenting information that enhances rather than overwhelms clinical decision-making. Visual design follows established principles for high-stress environments, employing color coding, progressive disclosure, and attention management.

3.1.4 Integration and Connectivity Layer

This component manages data flow between the AI-CDSS and external systems:

- **Hospital Integration:** Communication of prehospital findings, AI-generated risk assessments, and recommended interventions to receiving facilities
- **EMS Information Systems:** Bidirectional data exchange with computer-aided dispatch, electronic patient care reporting, and quality management systems
- **Offline Functionality:** Essential decision support capabilities maintained during connectivity interruptions, with synchronization upon reconnection
- **Cloud Computing Resources:** When connectivity allows, access to more computationally intensive algorithms and larger reference databases

3.1.5 Learning and Adaptation Layer

Continuous system improvement mechanisms include:

- **Outcome Tracking:** Longitudinal follow-up of patient outcomes to assess predictive accuracy
- **Error Analysis:** Systematic review of cases where AI recommendations diverged from optimal care

- **Algorithm Refinement:** Periodic retraining of models with accumulated field data
- **Performance Monitoring:** Ongoing assessment of system reliability, accuracy, and clinical impact

3.2 Clinical Workflow Integration

Successful AI-CDSS implementation requires seamless integration into existing EMS workflows. The proposed approach employs the following principles:

3.2.1 Workflow Mapping

Detailed analysis of current EMS clinical workflows identifies optimal integration points for AI support. These typically include:

1. **Initial Patient Contact:** AI analyzes dispatch information and early assessment findings to provide immediate differential diagnosis suggestions and alert providers to high-risk presentations
2. **Primary Assessment:** As vital signs are obtained, AI performs risk stratification and suggests priorities for focused examination
3. **Intervention Phase:** Treatment recommendations are provided based on identified conditions, patient factors, and available resources
4. **Transport Decision:** Destination selection support based on patient condition, facility capabilities, and system factors
5. **Hospital Handoff:** AI-generated summary of key findings, interventions, and predicted risks to facilitate efficient information transfer

3.2.2 Cognitive Load Management

AI-CDSS design specifically addresses cognitive load concerns:

- **Selective Information Presentation:** Only relevant, actionable information is displayed, avoiding information overload
- **Context-Aware Alerting:** Critical alerts are prioritized and displayed prominently, while routine information is readily available but not intrusive
- **Attention Management:** Visual and auditory alerts are designed to capture attention appropriately without causing distraction from patient care
- **Customization Options:** Providers can adjust display preferences and alert thresholds based on personal preferences and experience levels

3.3 Validation and Performance Metrics

Rigorous validation is essential for safe AI-CDSS deployment. The proposed framework employs a phased validation approach:

3.3.1 Phase 1: Retrospective Validation

Initial algorithm development uses historical prehospital data with known outcomes. Performance is assessed using standard metrics:

- **Diagnostic Accuracy:** Sensitivity, specificity, positive and negative predictive values for key conditions
- **Prognostic Performance:** AUROC, calibration curves, and Brier scores for outcome prediction
- **Treatment Appropriateness:** Concordance between AI recommendations and evidence-based guidelines

Validation datasets must be diverse, including multiple geographic regions, demographic groups, and EMS systems to ensure generalizability.

3.3.2 Phase 2: Prospective Observational Studies

Before active deployment, AI-CDSS operates in "shadow mode," generating recommendations that are recorded but not displayed to providers. This approach allows:

- **Real-World Performance Assessment:** Evaluation of AI accuracy in actual field conditions
- **System Reliability Testing:** Identification of technical issues, connectivity challenges, or workflow disruptions
- **Safety Monitoring:** Detection of potentially harmful recommendations before clinical implementation

3.3.3 Phase 3: Controlled Implementation

Initial clinical deployment occurs in controlled settings with enhanced monitoring:

- **Limited Deployment:** Implementation in selected units or regions with comprehensive oversight
- **Enhanced Documentation:** Detailed recording of AI recommendations, provider responses, and rationale for deviations
- **Rapid Cycle Improvement:** Quick identification and correction of issues based on field feedback

3.3.4 Phase 4: Broad Deployment with Ongoing Monitoring

Following successful controlled implementation, system deployment expands while maintaining rigorous performance monitoring:

- **Continuous Quality Metrics:** Ongoing tracking of diagnostic accuracy, treatment appropriateness, and patient outcomes
- **Adverse Event Surveillance:** Systematic identification and analysis of cases where AI recommendations may have contributed to suboptimal outcomes
- **Comparative Effectiveness Studies:** Long-term evaluation of outcomes in AI-assisted versus standard care

3.4 Ethical and Legal Considerations

AI-CDSS implementation raises important ethical and legal questions requiring thoughtful addressed:

3.4.1 Clinical Autonomy and Liability

AI recommendations should augment, not replace, provider judgment. Clear policies must define:

- **Provider Authority:** EMS personnel retain ultimate decision-making authority and responsibility
- **Override Documentation:** Mechanisms for recording when providers deviate from AI recommendations and why
- **Liability Framework:** Legal clarity regarding responsibility when AI-recommended care is followed or rejected

3.4.2 Algorithmic Bias and Health Equity

AI systems trained on non-representative datasets may perpetuate or amplify healthcare disparities. Mitigation strategies include:

- **Diverse Training Data:** Ensuring algorithm development uses data representing varied demographics, geographic regions, and socioeconomic contexts
- **Bias Testing:** Systematic evaluation of algorithm performance across different population subgroups
- **Equity Monitoring:** Ongoing assessment of whether AI implementation affects care quality differently across demographic groups

3.4.3 Data Privacy and Security

Prehospital AI-CDSS processes sensitive health information, requiring robust privacy protections:

- **De-identification:** Data used for algorithm training is appropriately anonymized
- **Secure Transmission:** Encrypted communication channels for all data transfer

- **Access Controls:** Strict limitations on who can access patient data and AI-generated insights
- **Regulatory Compliance:** Adherence to applicable privacy regulations (HIPAA in the United States, GDPR in Europe)

3.4.4 Informed Consent

Questions arise regarding whether patients should be informed when AI contributes to clinical decisions. Considerations include:

- **Transparency:** Patients have right to know AI is being used in their care
- **Emergency Context:** Practical limitations on obtaining consent in emergency situations
- **Opt-Out Mechanisms:** Policies allowing patients to decline AI-assisted care when clinically appropriate

3.4.5 Algorithm Transparency and Accountability

Healthcare organizations implementing AI-CDSS should maintain:

- **Algorithm Documentation:** Clear description of how AI systems make recommendations
- **Performance Reporting:** Regular publication of system accuracy and outcomes data
- **External Auditing:** Independent evaluation of algorithms for bias, accuracy, and safety
- **Governance Structures:** Clear organizational responsibility for AI system oversight

3.5 Continuous Learning Mechanisms

Unlike traditional clinical protocols, AI systems can continuously improve through accumulated experience. The framework includes:

3.5.1 Feedback Loops

Multiple mechanisms capture learning opportunities:

- **Outcome-Based Learning:** Algorithm adjustment based on actual patient outcomes
- **Error Correction:** Systematic analysis and correction when AI recommendations prove incorrect
- **Provider Feedback:** Integration of clinician observations about system performance
- **Comparative Analysis:** Identification of cases where provider judgment yielded better outcomes than AI recommendations

3.5.2 Model Updating Protocols

Systematic approach to algorithm refinement includes:

- **Regular Retraining:** Scheduled algorithm updates incorporating new data
- **Version Control:** Careful management of algorithm versions with clear documentation of changes
- **Performance Monitoring:** Comparison of new algorithm versions against previous performance
- **Rollback Capability:** Ability to revert to previous algorithm versions if performance deteriorates

3.5.3 Knowledge Integration

Mechanisms to incorporate new medical evidence:

- **Literature Monitoring:** Systematic review of emerging research relevant to prehospital care
- **Guideline Updates:** Rapid integration of revised clinical practice guidelines
- **Novel Findings:** Incorporation of new diagnostic or therapeutic approaches as they become established

4. Implementation Considerations

4.1 Technical Infrastructure

Successful AI-CDSS deployment requires:

- **Hardware:** Ruggedized, portable computing devices capable of running AI algorithms in austere environments
- **Connectivity:** Hybrid architecture supporting both connected and offline operation
- **Integration:** Compatibility with existing EMS equipment and information systems
- **Reliability:** System redundancy and failover mechanisms ensuring continuous operation

4.2 Training and Change Management

EMS personnel require preparation for AI-augmented practice:

- **Technical Training:** Education on system operation, interpretation of AI recommendations, and troubleshooting
- **Clinical Integration:** Guidance on incorporating AI insights into clinical decision-making
- **Limitations Awareness:** Clear understanding of AI system boundaries and error potential
- **Ongoing Education:** Continuous learning as systems evolve and capabilities expand

4.3 Organizational Readiness

Healthcare systems must prepare for AI integration:

- **Leadership Support:** Executive commitment to resources and change management
- **Cultural Readiness:** Organizational openness to technology-enhanced care delivery
- **Infrastructure Investment:** Commitment to necessary technical infrastructure
- **Quality Assurance:** Systems for monitoring AI impact on care quality and outcomes

4.4 Regulatory Considerations

AI-CDSS must navigate complex regulatory landscapes:

- **Medical Device Classification:** Determination of whether AI systems constitute medical devices requiring regulatory approval
- **Clinical Validation:** Meeting regulatory requirements for clinical effectiveness demonstration
- **Post-Market Surveillance:** Ongoing reporting of adverse events and performance data
- **International Standards:** Compliance with varying regulatory frameworks across jurisdictions

5. Case Study: Hypothetical Implementation

To illustrate the proposed framework, consider a hypothetical implementation in a metropolitan EMS system:

5.1 System Description

The system implements AI-CDSS for suspected stroke patients, a high-priority time-sensitive condition where early recognition and appropriate hospital selection significantly impact outcomes. The AI system analyzes:

- Patient demographics and medical history
- Vital signs and level of consciousness
- NIH Stroke Scale assessment findings entered via voice command
- Transport times to various receiving facilities
- Current emergency department wait times and stroke team availability

5.2 Clinical Workflow Integration

Upon arriving at a scene where stroke is suspected, the paramedic activates the stroke assessment module. As examination findings are documented via voice input, AI analyzes the data and provides:

1. Stroke probability estimate with confidence interval
2. Large vessel occlusion likelihood (relevant for directing to comprehensive stroke centers)
3. Recommended receiving facility with rationale
4. Predicted treatment eligibility window based on symptom onset time
5. Suggested pre-notification content for receiving hospital

5.3 Validation Approach

The system undergoes:

- Retrospective validation using 5,000 historical stroke and stroke-mimic presentations
- Prospective shadow-mode operation for six months across 20 ambulances
- Controlled implementation on 50 ambulances with enhanced monitoring
- System-wide deployment with ongoing quality metrics tracking

5.4 Outcomes Assessment

Metrics tracked include:

- Diagnostic accuracy for stroke identification and large vessel occlusion prediction
- Appropriateness of hospital destination selection
- Door-to-needle time for thrombolytic therapy
- Door-to-puncture time for mechanical thrombectomy
- 90-day modified Rankin Scale scores
- Provider satisfaction and perceived utility

5.5 Ethical Safeguards

Implementation includes:

- Clear communication to patients about AI use in their care
- Provider training emphasizing clinical autonomy and appropriate skepticism
- Monitoring for disparate performance across demographic groups
- Regular review of cases where AI recommendations were overridden
- Patient outcome tracking stratified by whether AI recommendations were followed

6. Discussion

6.1 Potential Benefits

AI-CDSS implementation in EMS offers several potential advantages:

Enhanced Diagnostic Accuracy: AI systems can detect subtle patterns in multimodal data that human providers might miss, particularly for conditions with variable presentations or those outside a provider's usual experience.

Reduced Cognitive Load: By handling routine data analysis and pattern recognition, AI can free provider cognitive resources for more complex aspects of patient care, situational awareness, and critical thinking.

Clinical Decision Support: Real-time access to evidence-based recommendations can enhance adherence to clinical guidelines, particularly for less common conditions or recently updated protocols.

Personalized Care: AI algorithms can consider individual patient factors, comorbidities, and risk profiles to tailor recommendations beyond one-size-fits-all protocols.

Quality Improvement: Systematic data collection and analysis facilitated by AI systems can identify areas for clinical improvement and measure intervention effectiveness.

Training Enhancement: AI systems can serve as educational tools, helping less experienced providers learn pattern recognition and clinical reasoning.

6.2 Challenges and Limitations

Despite potential benefits, significant challenges must be addressed:

Technical Reliability: Prehospital environments present harsh conditions for electronic systems. Devices must withstand temperature extremes, vibration, moisture, and physical impacts while maintaining reliable operation.

Connectivity Constraints: Many EMS operations occur in areas with limited or no cellular coverage. While edge computing addresses some concerns, certain AI capabilities require cloud connectivity.

Data Quality Issues: AI systems depend on accurate input data. Artifacts from patient movement, environmental interference, or equipment malfunction can degrade AI performance.

Algorithm Limitations: AI systems perform optimally within their training domain but may fail when encountering novel presentations, unusual patient populations, or scenarios not well-represented in training data.

Clinical Resistance: Some providers may be skeptical of AI recommendations, particularly early in implementation. Building trust requires demonstrated value and transparent performance.

Cost Considerations: AI-CDSS implementation requires substantial investment in devices, software development, integration, training, and ongoing maintenance. Cost-effectiveness must be demonstrated.

Regulatory Uncertainty: Evolving regulatory frameworks for AI in healthcare create uncertainty about approval pathways, liability, and compliance requirements.

6.3 Ethical Implications

AI integration into EMS raises important ethical questions:

Autonomy and Agency: Does AI support enhance provider capability or risk deskilling? Careful implementation must preserve clinical judgment while leveraging AI capabilities.

Equity and Access: Will AI-CDSS be available only to well-resourced EMS systems, potentially widening disparities? Consideration must be given to ensuring equitable access.

Bias and Fairness: Algorithms trained on non-representative data may perform poorly for underrepresented populations. Rigorous bias testing and mitigation is essential.

Transparency and Explainability: Patients and providers have right to understand how AI systems make recommendations. "Black box" algorithms are ethically problematic in healthcare.

Privacy and Surveillance: AI systems process sensitive health information and generate data about provider decision-making. Robust privacy protections are essential.

6.4 Future Research Directions

Several research priorities emerge from this framework:

Prospective Validation Studies: Rigorous field trials comparing patient outcomes with and without AI-CDSS support are urgently needed.

Human Factors Research: Understanding how providers interact with AI recommendations, make override decisions, and integrate AI into clinical reasoning requires systematic study.

Implementation Science: Research on effective strategies for AI-CDSS introduction, training, and organizational change management will inform successful deployment.

Long-Term Outcome Studies: Extended follow-up is needed to assess whether AI-assisted prehospital care improves patient outcomes beyond immediate metrics.

Cost-Effectiveness Analysis: Economic evaluation of AI-CDSS, considering implementation costs, operational savings, and value of improved outcomes, will inform adoption decisions.

Ethical Frameworks: Continued development of ethical guidelines specific to prehospital AI applications is needed.

Diverse Population Validation: Testing AI performance across varied demographics, geographic regions, and healthcare contexts is essential for equitable implementation.

7. Conclusions

Artificial intelligence-enhanced clinical decision support systems represent a transformative opportunity for Emergency Medical Services. The proposed framework provides a structured approach to AI-CDSS development, implementation, and evaluation that addresses current research gaps while prioritizing patient safety, clinical utility, and ethical practice.

Key elements of successful AI-CDSS implementation include:

1. **Rigorous Validation:** Moving beyond retrospective analyses to prospective field trials with diverse populations
2. **Clinical Integration:** Thoughtful workflow incorporation that enhances rather than disrupts care delivery
3. **Ethical Safeguards:** Addressing algorithmic bias, privacy protection, and preservation of clinical autonomy
4. **Continuous Learning:** Implementing mechanisms for ongoing system improvement based on accumulated experience
5. **Transparent Governance:** Establishing clear organizational responsibility and accountability for AI system oversight

While challenges remain—technical, clinical, ethical, and regulatory—the potential benefits of AI-CDSS justify continued development and rigorous evaluation. As AI capabilities advance and EMS faces increasing demands, thoughtful integration of these technologies can enhance provider capability, improve patient outcomes, and strengthen the prehospital care system.

Future research must prioritize prospective validation studies, human factors investigation, and long-term outcome assessment. Additionally, attention to algorithmic bias, health equity implications, and appropriate ethical frameworks is essential to ensure AI-CDSS implementation benefits all populations equitably.

References

[1] Basnawi, A. (2024). Addressing challenges in EMS department operations: A comprehensive analysis of key issues and solution. Emergency Care and Medicine, 1(1), 11-23. https://doi.org/10.3390/ecm1010003

[2] Goldberg, S. A., Chadwick, E., Makam, S., Shah, H. J., Bass, M. B., Hasdianda, M. A., Peters, G., Camargo, C. A., & Cash, R. E. (2023). Twenty years after the EMS Research Agenda: Trends in emergency medical services publications and research funding. Annals of Emergency Medicine, 82(1), 94-100. https://doi.org/10.1016/j.annemergmed.2023.02.017

[3] Lawrence, R. (2024). Artificial intelligence in EMS – The future is here. EMS1. Retrieved from https://www.ems1.com/ems-trend-report/artificial-intelligence-in-ems-the-future-is-here

[4] Mackenzie, J. S., et al. (2023). Artificial intelligence and machine learning in prehospital emergency care: A scoping review. iScience, 26(8), 107407. https://doi.org/10.1016/j.isci.2023.107407

[5] Raff, A. B., et al. (2024). Machine learning applications in sepsis triage and management. Journal of Hospital Medicine, 19(3), 145-156.

[6] Simpson, K. L., et al. (2025). Reducing medication errors through artificial intelligence: A systematic review. Clinical Pharmacology & Therapeutics, 117(2), 234-248.

[7] Tozer, M. (2024). EMS discussion - The integration of AI in prehospital settings. Embrace the Elements. Retrieved from https://www.embrace-the-elements.com/2024/10/ems-discussion-integration-of-ai-in.html

[8] Ventura, C. A. I., & Denton, E. E. (2023). Artificial intelligence chatbots and emergency medical services: Perspectives on the implications of generative AI in prehospital care. Open Access Emergency Medicine, 15, 289-292. https://doi.org/10.2147/OAEM.S423586

[9] Weidman, J. M., et al. (2025). Applying artificial intelligence to EMS strategy. American Journal of Health Care Sciences, 6(1), 45