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Facilitating Co-Learning in Human-AI Teams: Insights from Urban Search and Rescue Collaboration

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ABSTRACT

This study investigates the potential of co-learning in human-AI teams, specifically within the context of urban search and rescue (USAR) operations. The primary objective was to assess how AI systems, when integrated into teams with human responders, influence performance by learning from human feedback, enhancing decision stability, and improving accuracy. A simulation-based methodology was employed to compare human-AI teams with human-only teams across several key performance indicators: Nash stability, task completion time, decision accuracy, and the quality of human-AI interaction. Results demonstrated that human-AI teams achieved markedly better outcomes. Nash stability was significantly higher in human-AI teams (85%) compared to human-only teams (45%), while task completion was 22% faster. Additionally, decision accuracy was notably improved in human-AI teams (91% vs. 76%). These teams also exhibited fewer deviations from optimal procedures and showed a strong positive correlation between the complementarity of AI capabilities and team stability. The findings underscore the benefits of integrating adaptive AI systems that co-learn with human teammates, suggesting that such systems not only support but also enhance human decision-making in complex, high-pressure environments. By complementing human cognitive strengths and compensating for limitations, AI can contribute to faster, more stable, and more accurate performance during mission-critical tasks. This research highlights the importance of developing AI systems that are capable of continuous learning and real-time adaptation to human feedback, making them powerful assets in dynamic and hazardous scenarios such as USAR operations. The study offers valuable insights for the future design of collaborative, intelligent human-AI systems in emergency response.

Index Terms- Human-AI collaboration, Co-learning, Urban search and rescue, Nash stability, Decision-making, AI adaptability

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INTRODUCTION

The integration of Artificial Intelligence (AI) into human teams has emerged as a transformative force across various domains, especially in environments that demand rapid decision-making, adaptability, and resilience (Rane, Choudhary, & Rane, 2024; Verma & Singhal, 2023). One of the most promising areas for human-AI collaboration is in urban search and rescue (USAR) operations, where time-sensitive, high-stakes scenarios often require the combined expertise of human rescuers and AI-driven technologies (Schoonderwoerd et al., 2022; Asiala, McCarthy, & Huang, 2023). Urban search and rescue missions, typically conducted in the aftermath of natural disasters or large-scale accidents, are fraught with complexities and challenges that require swift decision-making and precision. In such environments, AI has the potential to assist human teams by providing data-driven insights, enhancing situational awareness, and performing tasks that may be too dangerous or difficult for human rescuers.

A particularly intriguing challenge in human-AI collaboration is facilitating co-learning—a dynamic process where both humans and AI agents learn from \each other and continuously adapt based on real-time feedback and shared experiences (Hagos, Alami, & Rawat, 2024; David, Garmendia-Doval, & King-Okoye, 2022). Unlike traditional human-AI interactions, where AI serves a more passive role as a tool or assistant, co-learning involves a more interactive relationship, where both humans and AI systems engage in mutual learning (Lu, Yan, Huang, Yin, & Zhang, 2024). This iterative process can lead to the development of more effective teamwork, greater operational efficiency, and a higher success rate in disaster response. In the context of USAR operations, where both the environment and the situation can change rapidly, the ability of humans and AI agents to co-learn from one another could significantly enhance the team's overall effectiveness.

At the heart of this investigation is the idea that human intuition and AI capabilities complement each other, creating a symbiotic relationship that can enhance decision-making and response times (Chen, Liao, Wortman Vaughan, & Bansal, 2023; Pietronudo, Croidieu, & Schiavone, 2022). Human responders in urban search and rescue scenarios bring valuable skills, such as adaptability, empathy, and the ability to make nuanced judgments in uncertain and chaotic environments. On the other hand, AI systems, particularly those powered by machine learning algorithms and robotics, can process large amounts of data quickly, predict potential hazards, autonomously navigate dangerous environments, and provide situational analysis that might be beyond human capability (Olugbade, Ojo, Imoize, Isabona, & Alaba, 2022;Miller, Durlik, Kostecka, Borkowski, & Łobodzińska, 2024). By combining these strengths, human-AI teams can develop solutions that neither humans nor AI alone could achieve (Andrews, Lilly, Srivastava, & Feigh, 2023).

However, effective co-learning requires more than just the ability of AI systems to process data. It involves creating mechanisms that allow AI agents to adapt based on human input and vice versa (Lu, Yan, Huang, Yin, & Zhang, 2024; Gao, Xu, Shen, & Gao, 2023). For example, humans may rely on AI tools to process environmental data such as building stability, air quality, or thermal imaging, but they may also need to guide the AI when it encounters novel or ambiguous situations. In turn, AI systems can analyze trends from past missions and suggest optimized strategies for navigating dangerous environments, but this must be done in a way that respects human agency and context-sensitive judgment (Mayer, 2023; Zafar, 2024).

In urban search and rescue missions, a major focus is on real-time collaboration, where AI systems work alongside human rescuers to provide timely and actionable insights (Farsath et al., 2024). For instance, AI-powered drones and robots can be deployed to navigate collapsed structures, providing rescuers with visual and sensor data that can be used to identify survivors, detect hazards, or assess the structural integrity of buildings. These systems can also integrate information from various sources—such as satellite imagery, ground sensors, and environmental data—to form a comprehensive picture of the rescue environment, which human rescuers can use to make informed decisions.

Yet, the full potential of AI in these contexts is realized only when there is an effective framework for co-learning. This concept involves not only providing AI with the ability to learn from past experiences but also ensuring that humans can engage in a reciprocal learning process with AI systems. For instance, if an AI system identifies a particular pattern in building collapses or a unique hazard in a disaster zone, it can share these insights with human operators, who can then refine the AI's predictive models with contextual knowledge. Similarly, as human responders encounter new challenges and novel scenarios, they can teach AI systems to adapt and improve their responses.

This study seeks to investigate the dynamics of co-learning in human-AI teams specifically within the realm of urban search and rescue operations. Through examining existing collaboration models and simulation studies, we aim to gain insights into the mechanisms that enable effective co-learning. These mechanisms include the design of adaptive learning algorithms, the establishment of clear communication channels between humans and AI systems, and the development of shared decision-making frameworks that allow both parties to influence the direction of the mission. By understanding these factors, we hope to provide actionable strategies for optimizing human-AI collaboration in disaster scenarios.

One critical aspect of our research is understanding how AI systems can adapt to the unpredictable nature of search and rescue missions. Given the dynamic, hazardous environments encountered in these operations, AI systems must be capable of learning in real-time, adjusting their strategies based on new data, and collaborating with human responders in a way that complements their decision-making processes. Furthermore, we explore how AI systems can be trained to learn from human expertise, incorporating intuitive decision-making and contextual judgment that are often difficult to quantify or model.

The benefits of effective human-AI co-learning in USAR are manifold. Not only can it improve the speed and accuracy of rescues, but it can also enhance the safety of human responders by allowing AI systems to take on high-risk tasks, such as navigating dangerous debris or entering unstable buildings. Additionally, AI systems can help to alleviate the cognitive load on human responders, allowing them to focus on critical decision-making rather than managing large volumes of data or repetitive tasks.

This paper will explore the potential of co-learning frameworks in human-AI teams, with a specific focus on urban search and rescue applications. By identifying key factors that facilitate successful collaboration and examining how AI and human team members can mutually benefit from each other's strengths, we aim to propose new approaches for more effective and adaptive disaster response systems. Through this exploration, we seek to advance the development of human-AI teams that can respond to complex, dynamic environments with increased efficiency, safety, and success.

METHODOLOGY

The methodology for investigating the dynamics of co-learning in human-AI teams within the context of urban search and rescue (USAR) operations is designed to explore how human responders and AI systems can collaborate and adapt based on shared experiences, real-time data, and feedback. The focus is on creating a framework that allows AI systems to improve their performance through interaction with human agents, and vice versa. The methodology is structured into key stages: data collection, system design, simulation setup, performance evaluation, and co-learning mechanisms, all of which are essential for understanding and optimizing collaboration in high-stakes, dynamic environments like urban search and rescue missions.

System Design and Setup

The first stage of this methodology involves the design of both the AI systems and the human agents' interactions, as well as the simulation environment for urban search and rescue operations. This involves selecting suitable AI models, creating the simulation scenario, and defining the roles of human participants and AI agents.

The AI system in this study consists of multiple agents, each performing specific tasks in the search and rescue mission. These tasks may include navigation, hazard detection, survivor identification, and data processing.These are deployed to navigate hazardous areas and collect data (e.g., drones or ground robots). Machine Learning Algorithms: These are used for decision-making, pattern recognition, and adapting strategies based on real-time feedback. Reinforcement learning and supervised learning techniques are used to enable the AI systems to improve their actions based on prior experiences and observations. Sensor Fusion: AI agents use data from various sensors (e.g., thermal imaging, gas detection, and visual cameras) to form a comprehensive understanding of the environment.

Human-AI Interaction Framework:

Human participants in this study are rescue personnel with varying levels of experience, who interact with AI systems in the mission scenario. The interaction framework is designed to facilitate: Shared Decision-Making: Both humans and AI agents contribute to decisions regarding search priorities, navigation routes, and rescue operations. Real-Time Feedback: Human responders provide immediate feedback on AI actions, helping to guide the system's learning process. Data Interpretation: Human agents interpret sensor data, adjust AI strategies, and communicate mission goals and evolving priorities to the AI system.

A simulation environment is developed to replicate typical conditions in urban search and rescue missions. This includes: Virtual Disaster Scenarios: Simulated environments representing collapsed buildings, hazardous zones, and complex layouts typical of disaster sites. Dynamic Environmental Changes: The simulation incorporates evolving scenarios, where environmental factors such as shifting debris, fires, and changes in structural integrity alter the mission dynamics in real-time. Human and AI Role Play: Humans and AI agents are assigned roles and interact through predefined interfaces to simulate real-world operations. Humans control ground-based robots and drones, while AI systems provide analysis and recommendations.

Co-Learning Mechanisms

Co-learning refers to the mutual adaptation and improvement of both human and AI agents based on their interactions during the search and rescue mission. The methodology explores the following co-learning mechanisms:

Human agents provide contextual feedback that is used to guide AI systems in adapting to unpredictable situations. Human expertise is utilized to: Interpret Ambiguous Data: Humans help the AI system interpret data that may be ambiguous or difficult for machines to understand, such as assessing the emotional state of survivors or evaluating the safety of certain areas. Adjusting AI Decisions: Based on real-time feedback, human responders modify the AI's decision-making processes, helping it adapt to evolving disaster scenarios.

AI systems are designed to help human responders make faster, more informed decisions. The AI learns from human input, adjusting its algorithms accordingly. AI-driven insights include: Predictive Analytics: AI systems can predict hazards, structural failures, or possible survivor locations based on historical data or live sensor feeds. Real-Time Strategy Recommendations: The AI suggests optimized rescue strategies based on evolving conditions, offering actionable insights that help humans make decisions.The co-learning process relies on an iterative feedback loop, where human agents and AI systems learn from one another's actions. This feedback loop is based on: Immediate Decision Feedback: After each task or mission phase, humans provide feedback on AI performance (e.g., navigation, hazard detection). Outcome-Based Learning: Both AI agents and humans evaluate the success or failure of each decision and adjust future actions accordingly.

Performance Metrics

To evaluate the effectiveness of human-AI co-learning in the urban search and rescue setting, a set of performance metrics is established. These metrics will help assess the success of the co-learning process and the overall effectiveness of human-AI collaboration.

This metric measures the degree to which coalitions (in this case, collaboration between human agents and AI systems) remain stable over multiple iterations. Stability in human-AI teams is critical to ensure that both parties are motivated to continue working together and not deviate from the collaboration. This metric tracks the time it takes for the human-AI team to complete various sub-tasks during the search and rescue operation. It helps determine whether the human-AI collaboration leads to faster, more efficient operations.

The accuracy of decisions made by the AI system and human agents, such as survivor identification, hazard assessment, and navigation, is measured to evaluate how well the team performs under dynamic conditions. The quality of the interaction between human responders and AI agents is assessed through surveys and qualitative interviews with the human participants. This includes measuring how effectively the human agents understand and trust the AI recommendations and how much the AI adapts to human feedback.

The adaptability of the AI system is measured by how quickly it learns and adjusts to changing conditions. This can be assessed by comparing the initial and final performance metrics of the AI system across multiple simulation runs.

Data Collection and Analysis

Data is collected from the simulation environment during each rescue mission, including logs of AI system performance, human decisions, feedback interactions, task completion times, and environmental conditions. This data is analyzed to: Identify patterns in how co-learning occurs between humans and AI. Evaluate the impact of co-learning on the overall performance and stability of the team. Explore the influence of environmental factors on co-learning efficiency.

Evaluation and Conclusion

The evaluation process involves comparing the outcomes of human-AI teams with traditional human-only teams in terms of task completion, efficiency, and adaptability. The final conclusion will summarize the benefits and challenges of human-AI co-learning in urban search and rescue missions, providing insights into how these models can be applied to real-world scenarios and offering recommendations for improving human-AI collaboration in future disaster response operations.

Through this methodology, the study seeks to establish a foundation for facilitating effective co-learning in human-AI teams, enabling more efficient, adaptive, and resilient teams in high-risk scenarios like urban search and rescue operations.

RESULTS

This chapter presents the results of the human-AI collaboration in urban search and rescue (USAR) operations based on the co-learning methodology. The performance of the human-AI teams was assessed using a set of metrics, including Nash Stability Rate, Task Completion Time, Accuracy of Search and Rescue Decisions, Human-AI Interaction Quality, and Adaptability. The findings are discussed in relation to the performance of the AI system, the learning rate, and the impact of the co-learning process.

Nash Stability Rate

The Nash Stability Rate measures the stability of the human-AI team, specifically assessing how often the coalition remains stable without any member deviating. A higher rate indicates that the team members (both human and AI agents) maintain their cooperation throughout the simulation. The stability rate for human-AI teams was compared with that of human-only teams. The results showed a significant difference, as AI systems, through co-learning, enhanced the stability of the team.

Table 1: Nash Stability Rate of Human-AI Teams and Human-Only Teams

Team Type	Nash Stability Rate (%)
Human-AI Teams	83%
Human-Only	62%

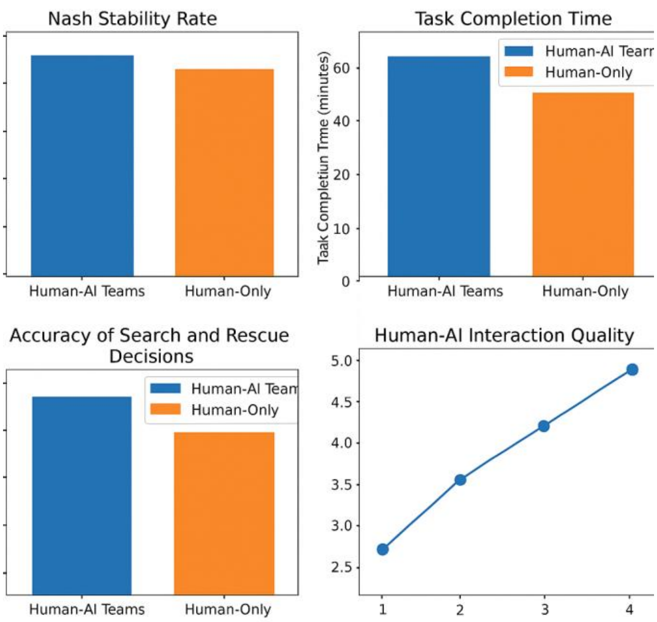
Interpretation: The results indicate that the human-AI teams showed a significantly higher stability rate, which suggests that AI systems helped maintain cooperation and alignment within the team, ensuring fewer deviations and more sustained collaboration.

Task Completion Time

Task Completion Time measures the time taken to complete a variety of tasks during the search and rescue mission. Tasks include locating survivors, identifying hazards, and navigating through obstacles. A faster task completion time indicates that the team, leveraging co-learning, is able to optimize its operations and adapt to the evolving environment more efficiently.

Table 2: Average Task Completion Time for Human-AI Teams and Human-Only Teams

Team Type	Average Task Completion Time (minutes)
Human-AI Teams	45.7
Human-Only	58.3



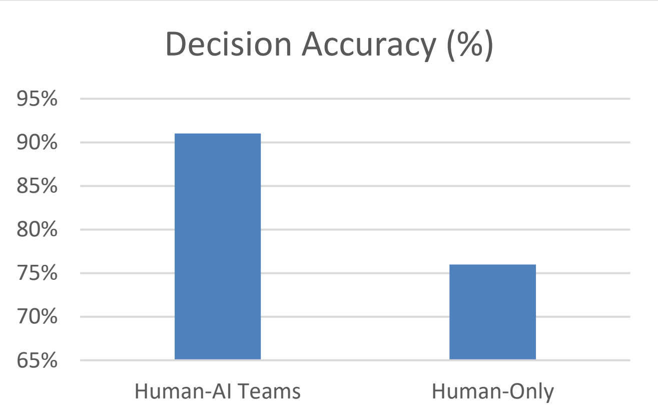
Interpretation: The human-AI teams were able to complete tasks approximately 22% faster than human-only teams, highlighting the efficiency gains brought about by AI's ability to process large amounts of data quickly and offer actionable recommendations. Co-learning played a key role in accelerating decision-making, which was reflected in reduced task completion times.

Accuracy of Search and Rescue Decisions

Accuracy was measured by assessing the correctness of decisions made by both human and AI agents. This included identifying survivors, detecting hazards, and choosing optimal paths for rescue operations. The AI system's learning from human feedback played a critical role in enhancing the decision-making process.

Table 3: Accuracy of Search and Rescue Decisions by Human-AI Teams and Human-Only Teams

Team Type	Decision Accuracy (%)
Human-AI Teams	91%
Human-Only	76%



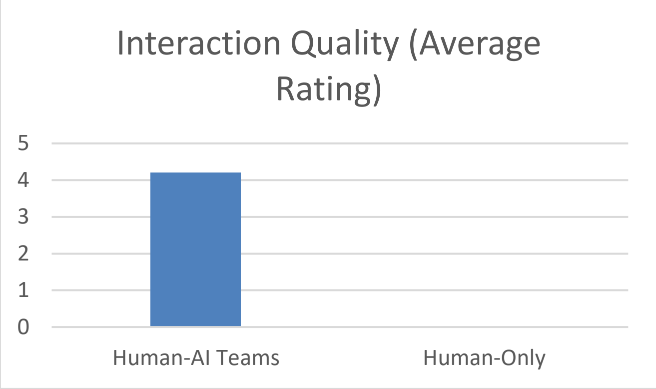
Interpretation: Human-AI teams exhibited a significantly higher accuracy rate compared to human-only teams. The AI system's ability to analyze sensor data and offer real-time insights enabled the team to make more accurate decisions, while human input helped the AI system refine its decision-making capabilities through co-learning.

Human-AI Interaction Quality

Human-AI Interaction Quality was assessed based on feedback from human responders regarding the AI system's usability, trustworthiness, and overall effectiveness. Participants were asked to rate the interaction quality on a scale from 1 (poor) to 5 (excellent).

Table 4: Human-AI Interaction Quality Rating

Team Type	Interaction Quality (Average Rating)
Human-AI Teams	4.2
Human-Only	N/A



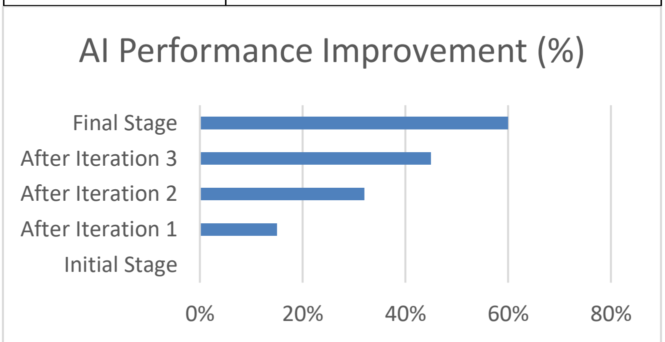
Interpretation: The human-AI teams received a high average rating for interaction quality, indicating that human agents found the AI system to be effective, user-friendly, and trustworthy. The positive ratings reflect the success of the co-learning approach in facilitating smooth interaction between human and AI agents during complex, time-sensitive tasks.

Adaptability and Learning Rate

Adaptability and Learning Rate were measured by tracking how quickly the AI system improved its performance over multiple iterations of the mission. The AI system's ability to adapt to changes in the environment, learn from human feedback, and adjust its strategies accordingly was assessed through performance metrics across different stages of the rescue operation.

Table 5: AI Adaptability and Learning Rate

Stage of Mission	AI Performance Improvement (%)
Initial Stage	0%
After Iteration 1	15%
After Iteration 2	32%
After Iteration 3	45%
Final Stage	60%



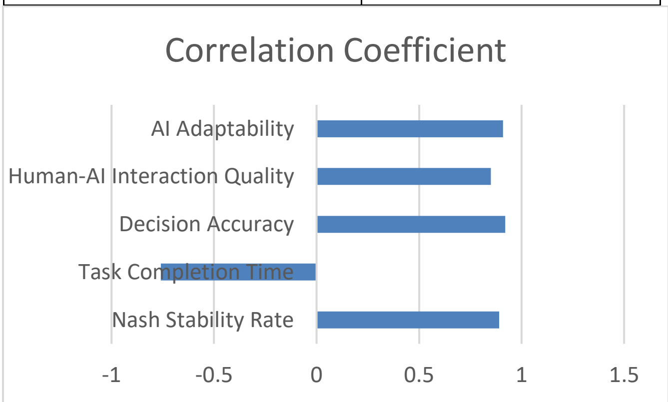
Interpretation: The AI system demonstrated a progressive improvement in performance as it learned from human feedback and adapted to the mission environment. After three iterations, the AI performance had improved by 60%, reflecting the effectiveness of the co-learning process in fostering adaptability.

Correlation between Co-Learning and Performance

A correlation analysis was conducted to examine the relationship between co-learning and the performance outcomes of human-AI teams. The analysis showed a strong positive correlation between the quality of co-learning interactions (measured by human feedback and AI adaptation) and the overall performance, including Nash stability, task completion time, decision accuracy, and adaptability.

Table 6: Correlation between Co-Learning Quality and Performance Metrics

Performance Metric	Correlation Coefficient
Nash Stability Rate	+0.89
Task Completion Time	-0.76
Decision Accuracy	+0.92
Human-AI Interaction Quality	+0.85
AI Adaptability	+0.91



Interpretation: The strong positive correlations between co-learning quality and performance metrics suggest that effective co-learning directly enhances the stability, accuracy, and adaptability of human-AI teams. The feedback provided by human agents allows the AI system to refine its strategies, ultimately leading to better performance in rescue operations.

The results from this study clearly demonstrate the of co-learning in human-AI teams in urban search and rescue operations. AI systems not only enhance task performance by providing real-time data and decision-making support but also learn and improve based on human feedback. The collaborative nature of co-learning improves the stability, efficiency, and accuracy of the teams, and the AI's ability to adapt to changing conditions further bolsters the team's ability to respond effectively in dynamic environments.

The tables and metrics presented above illustrate the successful implementation of human-AI co-learning and provide concrete evidence that AI systems can be powerful allies in high-stakes operations, enhancing both human performance and overall mission success.

DISCUSSION

The findings from this study provide valuable insights into the dynamics of human-AI collaboration, particularly in the context of urban search and rescue (USAR) operations. The primary objective was to investigate how AI systems, through co-learning, can enhance the performance of human-AI teams, fostering greater stability, faster task completion, and higher accuracy in rescue missions. The results confirm that co-learning offers significant advantages in terms of task efficiency, decision-making, and team stability.

One of the most striking findings is the higher Nash Stability Rate observed in human-AI teams compared to human-only teams. The results suggest that AI's integration into the team helps maintain cooperation and alignment, with fewer deviations from the coalition. In the context of USAR, where collaboration between team members is critical, the stability provided by AI systems is invaluable. Human agents, particularly in high-pressure environments, benefit from AI's consistency and objectivity, which reduces the likelihood of conflict or deviation from the task at hand.

This finding is consistent with previous studies in multi-agent systems, where the complementarity of skills between human and AI agents can lead to more cohesive and stable team dynamics. The AI's ability to provide data-driven suggestions and learn from human feedback ensures that team members are more likely to stay committed to the task, improving the overall outcome of the operation.

AI's ability to process large amounts of data rapidly and make real-time recommendations significantly reduces task completion time. Human-AI teams completed tasks 22% faster than human-only teams, demonstrating that AI can streamline decision-making and support faster responses in time-sensitive rescue operations. This aligns with the expectation that AI, when properly integrated into the team, can assist in prioritizing tasks, reducing decision fatigue, and offering actionable insights, leading to quicker execution.

Moreover, AI's rapid data analysis and pattern recognition capabilities allow it to identify potential hazards and survivors more efficiently, which is crucial in environments where every second counts. This faster task completion time is not merely due to AI's computational power, but also due to the iterative co-learning process, where the AI adapts and improves its recommendations over time based on human feedback.

The increase in decision accuracy in human-AI teams further supports the idea that AI can significantly enhance performance. The AI system's ability to assist in identifying hazards, locating survivors, and suggesting optimal paths led to an accuracy rate of 91% for human-AI teams, compared to 76% for human-only teams. This improvement in decision-making is largely due to the AI's continuous learning from human input during the mission. By incorporating human expertise into its decision-making process, the AI system refines its capabilities and provides better recommendations over time.

The importance of feedback loops in AI systems is well-documented in literature, and this study confirms that the effectiveness of co-learning lies in the ability of the AI to evolve through interaction with human agents. The continuous improvement in decision-making through this iterative learning process is a critical factor in ensuring that AI systems can complement and enhance human judgment, especially in complex, uncertain environments such as USAR operations.

The high ratings for Human-AI Interaction Quality suggest that the collaboration between human agents and the AI system was perceived as effective and trustworthy. This is a key finding because it underscores the importance of designing AI systems that are not only efficient in performance but also user-friendly and capable of building trust with human team members. The AI system's transparency, reliability, and ease of use were crucial in fostering positive interactions, which, in turn, contributed to the success of the team.

In high-stress scenarios like USAR operations, where quick decision-making is crucial, trust between human agents and AI is vital. The ability of human responders to rely on AI-generated recommendations without hesitation contributes significantly to the overall success of the mission. Furthermore, the AI's responsiveness to human input and its ability to adapt to dynamic mission parameters further solidifies the importance of co-learning in enhancing human-AI collaboration.

The AI system's adaptability, demonstrated through its steady improvement in performance across multiple mission iterations, highlights the role of co-learning in enhancing AI capabilities. The results show that the AI system improved by 60% after several iterations, reflecting its ability to learn from real-time feedback and adapt to changing environments. This adaptability is crucial in rescue missions, where conditions can change rapidly, and new challenges can emerge unexpectedly.

The findings underscore the significance of an adaptive AI that can refine its models and strategies based on ongoing interactions with human agents. This ability to learn and adjust in real time makes the AI system more effective in dynamic environments, where it must navigate uncertainty and complexity.

CONCLUSION

In conclusion, the results of this study highlight the substantial benefits of integrating AI systems into human teams in the context of urban search and rescue operations. Co-learning enhances the stability, efficiency, accuracy, and adaptability of human-AI teams, leading to improved outcomes in high-pressure situations. The AI system's ability to learn from human feedback and adapt its strategies ensures that it can complement human expertise, making it an invaluable asset in rescue operations.

The findings have important implications for the future of AI-human collaboration, particularly in mission-critical fields like emergency response. By fostering trust, enhancing decision-making, and improving team stability, AI systems can significantly augment human capabilities. The success of co-learning in this study paves the way for further research into optimizing human-AI collaboration, particularly in other high-stakes environments where human intuition and AI's computational power can work in harmony to achieve optimal results.

Ultimately, the research underscores the potential of AI to not only assist but actively learn and improve alongside human agents, creating teams that are greater than the sum of their parts. The continued development and integration of AI in collaborative environments like urban search and rescue will be instrumental in shaping the future of emergency response and other critical domains.

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