# AI-Driven Human-Autonomy Teaming in Tactical Operations: Proposed Framework, Challenges, and Future Directions

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Abstract—Artificial Intelligence (AI) techniques, particularly machine learning techniques, are rapidly transforming tactical operations by augmenting human decision-making capabilities. This paper explores AI-driven Human-Autonomy Teaming (HAT) as a transformative approach, focusing on how it empowers human decision-making in complex environments. While trust and explainability continue to pose significant challenges, our exploration focuses on the potential of AI-driven HAT to transform tactical operations. By improving situational awareness and supporting more informed decision-making, AI-driven HAT can enhance the effectiveness and safety of such operations. To this end, we propose a comprehensive framework that addresses the key components of AI-driven HAT, including trust and transparency, optimal function allocation between humans and AI, situational awareness, and ethical considerations. The proposed framework can serve as a foundation for future research and development in the field. By identifying and discussing critical research challenges and knowledge gaps in this framework, our work aims to guide the advancement of AI-driven HAT for optimizing tactical operations. We emphasize the importance of developing scalable and ethical AI-driven HAT systems that ensure seamless human-machine collaboration, prioritize ethical considerations, enhance model transparency through Explainable AI (XAI) techniques, and effectively manage the cognitive load of human operators.

*Keywords*—Artificial Intelligence, Human-Autonomy Teaming, Human-Machine Teaming, Tactical Operations

### I. INTRODUCTION

THE convergence of AI and autonomous technologies has revolutionized various industries, including defense and tactical operations. The rise of HAT can be attributed to several factors, including rapid advancements in autonomous technologies and AI [1], the increasing complexity of tasks and environments, the development of more capable autonomous systems, and the increasing availability of data and computing power [2]. As these technologies have become more sophisticated and capable, there has been a growing recognition of the potential collaborations that can be achieved by combining human cognitive abilities with the computational power and efficiency of autonomous systems [3]. The rise of modern HAT systems has also been driven by the need to address the complexities and challenges of rapidly evolving and dynamic environments. As tasks become more complex, time-sensitive, and data-intensive, the collaboration between humans and autonomous agents becomes crucial for effectively navigating and responding to these challenges.

HAT is an emerging field that explores collaborative partnerships between humans and autonomous systems to perform tasks or achieve common goals [2], [4]-[6]. This involves a collaborative arrangement in which at least one human worker collaborates with one or more autonomous agents [2]. This collaborative approach has the potential to revolutionize how tasks are accomplished across various sectors and pave the way for a future where humans and intelligent autonomous systems will work hand in hand to tackle complex problems and achieve shared goals. HAT systems are designed to allow humans to delegate tasks to intelligent autonomous agents while maintaining overall mission control [7]. Autonomous agents, in this context, refer to computer entities with varying degrees of self-governance in decision-making, adaptation, and communication. This definition has been supported by studies conducted by the research works in [8], [9]. The integration of human cognitive capabilities with the computational power and efficiency of autonomous systems in HAT enhances performance, decision-making, and overall system capabilities.

Here, we define and clarify some key concepts that are fundamental to understanding the scope and context of this study. These concepts include AI, Autonomy, Autonomous Systems, and Tactical Autonomy. By providing clear definitions and distinguishing between these terms, we aim to establish a common understanding among our readers.

Autonomy. Autonomy in the context of HAT describes the ability of intelligent autonomous systems or agents to operate and make decisions independently in a team setting with varying degrees of self-governance [3], [10]. This involves a higher degree of decision-making capability in autonomous systems based on learning, adaptation, and reasoning. It is a property of a system, not a technology itself [10]. An autonomous entity can perceive, reason, plan, and act in pursuit of specific goals or objectives without constant human intervention. It is important to note that the level of autonomy can vary, ranging from fully autonomous systems that make all their decisions to semi-autonomous systems that require human input at certain points [10]. In the context of tactical autonomy, HAT involves the integration of autonomous capabilities into tactical operations. This integration can include various applications, such as using autonomous systems to gather intelligence, perform surveillance, and perform other critical activities. Autonomy enables systems to operate in complex and uncertain environments, learn from experience, and make decisions without explicit human intervention in every scenario. However, it is important to distinguish this from traditional automation, which typically follows pre-programmed rules, decision trees, or logic-based algorithms to perform tasks or make decisions. Traditional automation has limited adaptability and flexibility to handle dynamic or unforeseen situations without explicit programming. This paper discusses how AI-driven autonomy differs from traditional automation by emphasizing learning, adaptation, and decision-making capabilities. These capabilities ultimately enhance the overall effectiveness and agility of human-autonomy teaming in tactical operations.

**Autonomous Systems**. Autonomous systems can perform tasks or operations without constant human control. They utilize AI algorithms and sensors to perceive and navigate their environment, achieving a high degree of autonomy [11].

**Tactical Autonomy**. In this study, tactical autonomy refers to autonomous systems' ability to make real-time decisions and take actions in dynamic and complex operational environments [12]. This involves the seamless coordination and interaction between humans and autonomous systems, enabling them to function as a unified team with complementary strengths [12]. HAT focuses on achieving shared mission goals through seamless coordination and collaboration between human operators and intelligent autonomous systems [13]. This paper introduces an AI-driven HAT, which integrates AI into HAT frameworks. This approach improves decision-making, situational awareness, and operational effectiveness by combining the strengths of human expertise and AI capabilities. Tactical autonomy, which combines human cognitive abilities, such as adaptability, intuition, and creativity, with the computational power, precision, and dynamic execution of autonomous systems, has the potential to revolutionize various fields, including defense, emergency response, law enforcement, and hazardous environments [12]. It is important to differentiate between tactical and strategic autonomy to clarify how AI-driven human-autonomy teaming contributes to both levels of autonomy in military and operational contexts. Strategic autonomy refers to a nation or organization's ability to make autonomous choices regarding broad security goals, whereas tactical autonomy, in contrast to strategic autonomy, focuses on individual units or teams acting independently within a specific mission [14]. Strategic autonomy involves higher-level decision-making and planning that considers long-term goals, overall mission objectives, and broader situational awareness. It addresses the coordination, allocation of resources, and strategic decision-making processes that guide the overall mission or campaign [14].

**Tactical Operations**. Tactical operations involve coordinated activities in a specific area or environment, typically in a military, law enforcement, or strategic context, focusing on achieving short-term objectives through rapid

decision-making, adaptation to dynamic situations, and the application of military skills and resources within a localized area and timeframe [15].

In recent years, advancements in AI, Machine Learning (ML), robotics, and sensor technologies have paved the way for realizing the potential of tactical autonomy [12]. These technological advancements have enabled autonomous systems to perform complex tasks, process vast amounts of data in real-time, make informed decisions, and collaborate with human team members seamlessly [12]. This has opened new possibilities for augmenting human capabilities, optimizing resource allocation, and improving overall operational efficiency. However, effective tactical autonomy requires a comprehensive understanding of the dynamics between humans and autonomous systems. Human factors, including trust, communication, shared situational awareness, and decision-making, play a vital role in ensuring successful HAT. Challenges such as establishing appropriate levels of trust, addressing potential cognitive biases, managing workload distribution, and maintaining effective communication channels must be carefully addressed to ensure seamless collaboration and maximize the potential benefits of tactical autonomy. HAT for tactical autonomy is a collaborative approach to using humans and autonomous systems to operate and control weapons and other military systems. In HAT, the human operators and autonomous systems work together to achieve common goals. The human operators are responsible for the overall mission and making high-level decisions. Autonomous systems are responsible for performing assigned tasks.

As explained in detail in Section IV, human operators contribute strategic insight, context, and high-level decision-making capabilities based on their experience and understanding of the mission's goals. The interaction and communication represent the interfaces and communication channels through which each component exchanges information, collaborates, and makes joint decisions. Within the context of a shared decision-making process, human operators and autonomous systems engage in a collaborative decision-making process, sharing insights, data, and recommendations to formulate effective strategies. The autonomous system is responsible for real-time data processing, analysis, and execution of specific tasks supporting human operators with timely and pertinent information. Subsequently, once decisions are made, the autonomous system performs specific tasks, including reconnaissance, navigation, or data collection, in alignment with the directives of the shared decision-making process.

This paper comprehensively explores the historical development and current state of HAT and delves into the opportunities, challenges, and potential future directions in leveraging AI for tactical autonomy. It emphasizes the transformative impact of AI on tactical autonomy and presents opportunities for improved decision-making, situational awareness, and resource optimization. By acknowledging and addressing the challenges associated with AI adoption, and by charting future directions for research, we can pave the way for a future where humans and autonomous systems

seamlessly collaborate, ultimately leading to safer, more efficient, and successful missions in tactical environments.

# A. Scope and Contributions

The main contribution of this paper is its forward-looking study of the applications, trends, and disruptive technologies that will drive the HAT revolution in complex and dynamic environments. This provides a clear picture of HAT services and practical recommendations for future work.

### **B.** Contributions

This paper makes the following key contributions to the field of HAT.

- We propose a comprehensive conceptual framework for AI-driven HAT in tactical operations, describing critical components such as trust and transparency, function allocation, situational awareness, and ethical considerations. The proposed framework provides a foundation to understand and advance the integration of AI into HAT for tactical environments.
- We provide a comprehensive overview of the opportunities and key challenges associated with incorporating AI-driven HAT into tactical operations.
- We explore the symbiotic relationship between AI and HAT, presenting a thorough analysis of how AI-driven HAT enhances decision-making, situational awareness, and operational effectiveness in tactical environments.
- We identify several research directions for future work in AI-driven HAT, emphasizing ethical considerations, building transparent AI models, and advancing human-centric design principles to fully realize the potential of tactical autonomy.

Table I compares our work to existing studies. In this paper, we explore and address research questions related to AI-driven HAT to enhance tactical operations, covering various aspects and challenges.

- How do AI and HAT benefit each other when achieving tactical autonomy?
- What are the main opportunities and challenges associated with incorporating AI-driven HAT in the context of tactical operations?
- How can AI-driven HAT be best used in tactical operations to improve success and decision-making?
- What is the plan for AI-driven HAT and how can it improve the collaboration between humans and autonomous systems in tactical situations?
- How can AI-driven HAT help humans and autonomous systems work together smoothly to achieve common goals in tactical environments?
- What ethical concerns must be considered when developing and using AI-driven HAT systems?
- How can we make AI models in HAT more understandable, and why does this matter for better decision-making and trust in autonomous systems?
- What design principles should be followed to create user-friendly AI-driven HAT systems for human operators in tactical settings?

# C. Methodology

This study investigates the potential of AI-driven HAT to revolutionize tactical operations. To achieve this, we conducted a systematic literature review to identify and analyze relevant academic research. Our search primarily targeted prominent academic databases such as Google Scholar, IEEE Xplore, ACM Digital Library, and ScienceDirect for scholarly articles published up to 2024. We focused on studies published up to May 2024 that emphasized empirical research and theoretical frameworks to explore the application of AI in human-autonomy teaming for tactical operations. Note that studies that focused on general AI applications without a tactical operation context were excluded. We employed a combination of keywords, including "AI-driven human-autonomy teaming," "tactical operations," "situational awareness," "automated decision-making," "Integrating AI and HAT," "situation models," and "shared situational awareness in HAT." We included studies that focused on the application of AI in HAT for tactical operations, explored the use of Natural Language Processing (NLP) and reinforcement learning for improved communication, collaboration, and threat assessment, and addressed challenges related to trust, explainability, and ethical considerations. Furthermore, we included studies that explored the impact of AI-driven HAT on trust, explainability, and ethical considerations. We employed thematic analysis to identify key themes emerging from the reviewed literature, focusing on the opportunities and challenges associated with AI-driven HAT, with a particular emphasis on enhancing situational awareness, decision-making, and human-machine collaboration.

The remainder of this paper is organized as follows. Section II discusses the integration of AI solutions into HAT. In Section III, we discuss the concept of delegated autonomy in HAT, exploring different levels and the balance between human decision-making and automated systems in teaming scenarios. Section IV presents the key components and characteristics defining HAT systems. Next, Section V identifies and discusses the practical applications of HAT, presenting real-world examples where HAT has proven advantageous. Section VI explores the economic aspects of AI integration in HAT. VII provides a detailed discussion of situation models and shared situational awareness in HAT. Section VIII outlines the specific roles and contributions of AI in enabling tactical autonomy in HAT, emphasizing its ability to enhance human decision-making. The opportunities and challenges associated with using AI to enhance HAT in tactical autonomy are discussed in Section X. The design of user interfaces and interaction mechanisms for HAT systems in tactical autonomy settings is explored in Section IX. Section XI introduces a proposed framework for AI-driven HAT in tactical operations, describes the key components, and provides guidance for future research and development. Finally, Section XII provides practical recommendations for implementing and optimizing HAT systems. The paper concludes in Section XIII with indications for future work.

Year	Publications	Main Research Focus and Scope
2018	Ref [16]	• Explores the relationship between team coordination dynamics and team performance for human-autonomy teams using an extended version of nonlinear dynamical systems methods.
2018	Ref [17]	• Proposed a framework for HAT, incorporating three key tenets: transparency, bi-directional communication, and operator-directed authority.
2019	Ref [18]	• Discusses what function allocation and challenges in allocating tasks between humans and autonomous machines.
2020	Ref [19]	• Provides a framework for practitioners to make informed decisions regarding the integration and training of human-autonomy teams in applied settings.
2020	Ref [20]	• Proposes a new approach to using ML agents in real-time strategy games to collaborate with human players rather than competing against them.
2021	Ref [3]	• Examines the differences between automation and autonomy and how insights from human-human teaming can be applied to HAT. The authors have identified research gaps that need to be addressed to improve the understanding of HAT.
2022	Ref [2]	• Provides a comprehensive understanding of the research environment, dependent variables, independent variables, key findings, and future research directions related to human-autonomy teamwork.
2022	Ref [21]	• Emphasizes the need for humans and AI to work together effectively, particularly in complex situations. It examines the factors affecting the design and implementation of AI systems for human interaction. In addition, it provides a detailed roadmap for future HAT research, particularly emphasizing the perspectives of human factors, which aligns well with our focus on enhancing tactical operations through AI-driven HAT.
2024	Our Paper	<ul> <li>Proposes a comprehensive conceptual framework for AI-driven HAT in tactical operations, detailing critical components, such as trust and transparency, function allocation, situational awareness, and ethical considerations.</li> <li>Explores the advantages and challenges associated with integrating AI-powered HAT into tactical operations.</li> <li>Provides a thorough exploration of the symbiotic relationship between AI and HAT in the context of tactical operations.</li> <li>Identifies several research directions, including ethical considerations, building transparent AI models, and advancing human-centric design principles, for future work in AI-driven HAT.</li> </ul>

TABLE I: Comparison of our work to existing works.

# II. MOTIVATION

In this section, we describe the motivation for the integration of AI solutions within HAT, highlighting their transformative impact on collaboration, communication, and coordination in dynamic and complex tactical environments.

HAT is a rapidly evolving field that seeks to combine the strengths of humans and autonomous systems to achieve common goals. In recent years, the convergence of AI and HAT has emerged as a paradigm-shifting approach with the potential to revolutionize decision-making, situational awareness, and operational efficiency in dynamic and complex tactical environments. In tactical autonomy, HAT revolutionizes how humans and machines work together in dynamic and complex environments. The integration of AI solutions into HAT offers a compelling avenue to enhance the strengths of both human operators and intelligent autonomous systems, which is promising to advance tactical autonomy. This paper underscores the significance of this integration and presents opportunities, challenges, and directions for future work. We envision a landscape in which the symbiotic relationship between humans and autonomous systems can reshape tactical decision-making, enhance situational awareness, and maximize operational efficiency. By focusing on its transformative impact, this paper sets the stage for a future where collaboration, communication, and coordination in dynamic and complex tactical environments can be elevated to new heights, ultimately contributing to safer and more successful mission outcomes.

**Collaboration**. At the core of AI-driven HAT lies a new era of collaboration that redefines the possibilities of human operators and intelligent autonomous systems

working together [22]. AI technologies serve as bridges that enhance collaboration by boosting human capabilities through data-driven insights and analytical power [23]. By seamlessly integrating AI solutions into the decision-making process, HAT systems can leverage real-time data analysis, predictive analytics, and pattern recognition to provide human operators with a comprehensive and dynamic understanding of the tactical situation [23]–[26]. This improved collaboration enables operators to make informed decisions more quickly, which is often critical in tactical environments where split-second choices can impact mission success [24]–[26].

Communication. Effective teamwork relies on empowering communication, and within the context of tactical autonomy, the integration of AI introduces a new dimension to this foundational aspect [27]. NLP and intelligent communication interfaces enable HAT systems to facilitate seamless interactions between humans and autonomous agents. Conversational AI, chatbots [28], and language translation tools enable real-time communication [29], transcending language barriers and fostering a more inclusive and collaborative environment. This enhanced communication enables operators to convey complex instructions, receive real-time updates, and seek clarifications, thus simplifying the decision-making processes and reducing ambiguity in high-stress scenarios. As described by Shively et al. [17], HAT also incorporates a bi-directional communication approach, which transforms automation from a tool to a teammate. This dynamic communication enables collaborative problem-solving, enabling seamless interactions and joint decision-making between automated systems and human operators.

**Coordination**. In dynamic and complex tactical environments, humans and autonomous systems must effectively coordinate their actions effectively [16]. Precise coordination in dynamic and complex tactical environments requires a level of precision that traditional approaches often struggle to achieve. AI-driven HAT transforms coordination into a finely tuned orchestration of human and autonomous actions. Autonomous agents equipped with reinforcement learning and multi-agent systems can execute tasks with adaptability and accuracy, aligning their actions with human operator intentions. This coordination optimizes resource allocation, minimizes response times, and ensures that tasks are executed efficiently, even in the face of unforeseen challenges. The result is a synchronized team that capitalizes on each member's strengths and operates in harmony to achieve the mission objectives.

# III. DELEGATED AUTONOMY IN HAT

As technology advances, the integration of autonomy into various domains has become more prevalent [30]. Delegated autonomy, which is a critical concept in HAT, entails granting autonomous systems a certain level of decision-making authority while maintaining human oversight based on predefined rules, constraints, or algorithms [31]. The degree of autonomy granted to machines can vary based on task complexity, system capabilities, and the context of the operation. Humans retain the ability to intervene, monitor, and override autonomous decisions when necessary, thus ensuring accountability and preventing potential errors. Delegated autonomy generally refers to the ability or a situation in which a human operator dynamically assigns certain tasks or responsibilities to an autonomous system, thereby allowing the system to operate independently within specified constraints [32]. This can be achieved in various ways, depending on the specific tasks or responsibilities being delegated. The following are some practical examples of delegated autonomy.

**Unmanned Aerial Vehicles (UAVs)**. In the field of aviation, UAVs often operate with delegated autonomy. Autonomous drones can follow pre-planned flight paths, avoid obstacles, and adapt to changing weather conditions, while human operators maintain the authority to intervene in situations that require human judgment [33]. Studies have shown that HAT systems can perform effectively in unmanned settings for search and rescue [34], [35], infrastructure inspection [36], [37], and agriculture and traffic monitoring [38], [39].

**Robotic Systems**. Robots are being used in various industries, from manufacturing [40], [41] to healthcare [42]. In the context of robotic systems, surgical robots exemplify delegated autonomy in healthcare and other domains [43]. In the context of medical robots, a human surgeon delegates some of their autonomy to the robot, allowing it to perform certain tasks without direct human intervention [44], [45]. Surgeons control robotic arms to perform precise movements during surgeries, while the system's autonomy assists in error correction and stabilizing movements. Some of the benefits of medical robots include increased precision and accuracy [45], [46], enhanced

efficiency [45], minimized human error [45], remote surgery and telemedicine [45], etc.

**Autonomous Vehicles**. Self-driving cars operate with varying degrees of delegated autonomy [47]. A vehicle's autonomous systems handle tasks like lane-keeping [48], [49] and adaptive steering control [50]–[53], while the human driver remains responsible for monitoring the environment and taking control when needed [47].

### IV. KEY COMPONENTS AND CHARACTERISTICS OF HAT

Understanding the key components and characteristics of Human-Autonomy Teaming (HAT) is important for exploring its wide-ranging applications, as discussed in Section V.

# A. Key Components of HAT

Based on [18], [27], [41], [54], [55], we identify the essential components and relevant aspects of integrating HAT in practical contexts. These components and aspects guide the understanding and implementation of human-autonomy interaction and teaming, thus providing suitable methodologies for conducting experiments [56].

**Human Operators**. The human component of HAT consists of competent skilled individuals with the necessary expertise, decision-making abilities, and interpersonal communication skills to achieve team goals [54]. Human workers engage in tasks requiring judgment, decision-making, creativity, and interpersonal communication [56].

**AI.** In HAT, AI plays a crucial role in augmenting human abilities and driving team performance by providing cognitive capabilities, such as perception, reasoning, and decision-making, which enable autonomous systems to operate effectively in complex environments [18]. Careful design and integration of AI algorithms are essential for the reliability, credibility, and transparency of HAT systems. For more details, refer to Section VIII.

**Autonomous Systems**. This aspect of HAT involves machinery, computer systems, or AI that can automate tasks and make predictions through AI algorithms [27]. Autonomous systems enhance human abilities, enabling them to focus on complex tasks and decision-making.

**Interfacing with Autonomous Systems**. Communication plays a vital role in HAT. An ontology-based communication language allows direct interactions between AI and autonomous systems. Effective communication in HAT is facilitated by a communication language ontology and domain ontologies [56]. These ontologies ensure seamless communication between humans, AI, and autonomous systems, thereby enhancing collaboration and data exchange [56].

# B. Characteristics of HAT

Research on HAT underscores the importance of team performance outcomes, collaboration processes, and effective training methods [41], [57]. Some of the main characteristics of HAT include:

**Heterogeneity**. HAT teams comprise diverse members with specific roles, and they leverage the strengths of AI systems to realize tasks that align with their capabilities [18].

**Shared Cognition**. Developing shared mental models promotes effective teamwork within HAT and enhances team understanding and performance [57]. This practice facilitates a deeper understanding of teammates' capabilities, limitations, objectives, and performance, thereby significantly facilitating efficient team processes and overall team performance. Moreover, developing shared mental models contributes to the establishment of shared situational awareness within teams [57].

**Collaboration and Communication**. Successful teamwork in HAT requires efficient collaboration and communication among humans, AI algorithms, and autonomous systems [27].

**Social Intelligence**. Leveraging social intelligence enhances the effectiveness of human team members' effectiveness in HAT, enabling team members to effectively understand and support teammates effectively [41].

# V. APPLICATIONS OF HAT

After identifying the essential building blocks of HAT in the previous section, we explore how HAT applications are revolutionizing various industries. HAT technology has the potential to revolutionize many industries. HAT systems leverage the strengths of humans and autonomous systems to perform tasks with greater accuracy, speed, and reliability [58]. These systems are increasingly being employed across various industries to exploit the strengths of humans and intelligent autonomous systems. These teams can improve safety, efficiency, and productivity across various domains. Figure 1 shows applications of HAT in modern life.

**Defense**. In modern military applications, HAT systems enable the seamless integration of human intelligence and strategic thinking with the speed, precision, and endurance of intelligent autonomous systems [24], [59]. This integration enhances situational awareness, mission effectiveness, and operational efficiency [24], [59]. By combining the strengths of humans and intelligent machines, AI has the potential to revolutionize military operations and make the world a safer place.

**Manufacturing**. HAT can optimize industrial processes by combining human expertise with automation [19]. Humans have cognitive abilities, problem-solving skills, and adaptability, and intelligent autonomous systems offer precision, strength, and speed [41].

**Healthcare**. HAT systems have the potential to revolutionize healthcare by assisting medical professionals in their work [60]. Modern HAT systems can be used to analyze medical images, such as X-rays and Magnetic Resonance Imaging (MRI) scans, to identify signs of disease. HAT systems can also be used to analyze patient data, such as blood test results and medical history, to help physicians make more accurate diagnoses.

Games. HAT principles can be applied to gaming to enhance player experiences by assisting with tasks that are difficult

or time-consuming for humans, creating more engaging gameplay, and exploring new ways of interaction between players and autonomous systems in a virtual environment [20], [61].

**Aviation and Space Exploration**. HAT is a promising technology with the potential to revolutionize aviation and space exploration [54]. In aviation, cockpit automation involves collaboration between pilots and autonomous systems to safely operate aircraft [62], [63].

**Transportation**. HAT can be applied to autonomous vehicles for passenger transportation and logistics. This involves collaboration between self-driving vehicles, human drivers, autonomous vehicles, and pedestrians in urban environments. In addition, HAT is considered essential for safe and efficient operation in the context of Urban Air Mobility (UAM) systems. UAM is an emerging concept that refers to using aerial vehicles, such as drones or small electric aircraft, to transport people and goods within urban environments [64]. HAT can play a crucial role in ensuring safe, efficient, and integrated operations within UAM systems.



Fig. 1: Applications of HAT.

# VI. THE ECONOMICS OF INTEGRATING AI AND HAT

Integrating AI and HAT for tactical autonomy brings about a range of economic benefits, particularly in domains where rapid and effective decision-making, enhanced situational awareness, and optimized resource utilization are critical. Although the potential of HAT applications across various industries is undeniable (Section V), a closer look at the economic impact of integrating AI and HAT is also important. This Section provides a detailed analysis of the potential economic benefits and challenges associated with such transformative collaboration. This study also examines the impact of AI-driven HAT on productivity, labor markets, cost-effectiveness, and overall economic growth. Additionally, the potential economic challenges and opportunities presented by the widespread adoption of HAT in various industries are highlighted.

# A. Economic Benefits of Integrating AI and HAT

Several potential economic benefits of HAT are discussed in prior studies [65], [66]. These benefits include enhanced productivity, safety, operational efficiency, and cost reduction. HAT enables human workers to concentrate on creative and strategic tasks.

**Improved productivity**. Effective collaboration between humans and autonomous systems can significantly improve productivity. Autonomous systems excel at performing repetitive tasks at high speed and accuracy, whereas humans contribute their expertise and decision-making skills, which are lacking in autonomous systems.

**Reduced Operational Costs.** Incorporating AI and HAT in tactical autonomy not only enhances the efficiency and effectiveness of critical missions but also contributes to substantial economic gains through reduced costs, increased success rates, and optimized resource utilization. Automation leads to cost reduction by delegating routine tasks, such as manufacturing, transportation, and customer service, to autonomous systems. This, in turn, allows human workers to concentrate on more creative and strategic tasks that demand problem-solving skills and creativity. Hence, automating routine and data-intensive tasks through AI-powered autonomous systems reduces labor costs and minimizes human intervention. These optimizations translate to significant operational cost savings.

**Improved Situational Awareness.** As explained below, AI enhances the information available to human operators, providing a comprehensive view of the tactical environment. This leads to better-informed decisions and minimizes the financial consequences of inadequate awareness.

**Scalability and Flexibility**. AI-driven intelligent autonomous systems can adapt to changing tactical conditions and complex requirements, enabling scalable operations without increasing human labor costs [19].

# B. Economic Challenges of Integrating AI and HAT

In addition to economic benefits, HAT presents potential economic challenges. One such challenge, for example, is job displacement because autonomous systems take over tasks currently performed by humans. In addition, increased reliance on autonomous systems can pose safety risks if they are not properly designed and operated. Here, we discuss some potential challenges in detail.

**Job displacement**. Automation could lead to job displacement because modern and intelligent autonomous systems can take over tasks currently performed by humans. This shift might hurt the economy, resulting in higher unemployment rates and lower wages.

Increased safety risks. HAT could lead to increased safety risks if autonomous systems are not properly designed and operated. For example, mistakes made by autonomous systems can result in accidents or injury.

**Privacy concerns**. Automation could raise privacy concerns because autonomous systems can collect and store large amounts of data about human users. These data could be used for marketing or other purposes without the user's consent.

# VII. SITUATION MODELS AND SHARED SITUATIONAL AWARENESS IN HAT

The economic analysis in Section VI highlighted the importance of efficient decision-making in HAT. However, effective decision-making requires a shared understanding of the situation. This section explores how situation models and shared situational awareness facilitate the flow of information required for human and autonomous systems to work together seamlessly.

### A. Situation Models of HAT

In the context of HAT, situation models and shared situational awareness play a crucial role in ensuring effective collaboration between humans and autonomous systems in complex environments [67]. Situation models represent an individual's internal understanding of the world, their experiences, and others. This understanding is dynamic and constantly updated based on sensory inputs and mental models (see Figure 2). For effective collaboration in complex environments, HAT requires humans, AI, and autonomous systems to develop internal situation models. Here, are the key aspects of the situation models in HAT.

**Situation**. Similar to how humans in Multi-Domain Operations (MDO) rely on situational awareness, AI algorithms must develop and maintain an accurate model of the world. This is crucial for informed decision-making [67]–[70]. Effective HAT systems emphasize shared mental models and team situational awareness. Advanced AI techniques can improve these aspects by providing humans with insights into the decision-making processes of machine learning models, further enhancing situational awareness and shared understanding [71].

**Task Environment**. A dynamic function allocation mechanism has been proposed for future HAT systems, where tasks are distributed among human and autonomous teammates based on their capabilities [18]. This requires an updated model of the work environment, including current goals, assignments, plans, and the state of humans and automation involved [7].

**Teammate awareness.** As humans must understand AI reliability, AI may require a model of the current state of its human teammates to perform assigned tasks effectively [72], [73].

**Self-awareness**. Being aware of one's capabilities is important. Team members who recognize fatigue, workload, or inadequate training can shift tasks to optimize performance [74], [75]. AI may need to develop a model of its performance

limitations to indicate when human intervention is needed or whether its calculations are accurate [68], [76].

These individual situation models are important for achieving shared situational awareness, which is the focus of the following subsection.

### B. Shared Situational Awareness

Situational awareness in HAT refers to individuals' and teams' ability to perceive, understand, and anticipate relevant information and events in their operational environment [77], [78]. This extends beyond human team members to include collaborative autonomous systems and robots. Developing shared situational awareness requires collaboration between humans, autonomous systems, and AI algorithms. Humans rely on sensory inputs such as vision and hearing, and autonomous systems rely on sensor data and AI algorithms for safety [77], [78]. Effective communication, information sharing, and collaboration are crucial for maintaining shared awareness over time in HAT. The following are some challenges to achieving shared situational awareness:

**Information Overload**. The vast amount of data generated by autonomous systems can overwhelm human agents [77], [79]. This makes it harder for users to concentrate on important tasks. HAT systems should provide mechanisms to filter and prioritize information, ensuring that human agents only receive relevant and actionable data [79].

**Cognitive Overload**. Processing large amounts of information while making decisions can lead to cognitive overload in human agents [77]. HAT systems can mitigate this by incorporating intelligent algorithms to facilitate data analysis and decision-making, which reduces the cognitive burden of humans.

**Training and Interfaces**. Effective use of tools and interfaces to facilitate shared situational awareness is crucial for human agents in HAT scenarios [80], [81]. These tools include dashboards, augmented reality displays, and communication systems that present relevant information. Training programs should cover not only technical aspects but also emphasize human-autonomy collaboration strategies and best practices. User-friendly interfaces and well-designed human-autonomy interaction mechanisms can also help reduce the learning curve and improve usability.

In summary, building a common operating picture through situation models and shared situational awareness is essential for effective HAT. By carefully managing information flow, providing appropriate training, and using well-designed interfaces, we can ensure successful collaboration between humans and autonomous systems.

### VIII. ROLES OF AI IN HAT FOR TACTICAL OPERATIONS

Section VII highlighted the importance of shared understanding in HAT. However, effectively processing the enormous amount of information required by such models is a critical challenge. This section explores how AI capabilities are leveraged in HAT to address this challenge, with a specific focus on tactical operations.

AI has created a revolutionary transformation in numerous domains and industries, introducing advanced capabilities previously beyond reach. In the medical and healthcare fields, for example, AI plays a pivotal role in disease diagnosis, treatment development, and personalized patient care [82]. Diagnostic AI-powered systems exhibit remarkable accuracy in interpreting medical images, such as X-ray and MRI images, thereby helping medical professionals make more informed decisions. These systems excel at analyzing complex medical images and identifying tumors or anomalies that human professionals may overlook. Additionally, AI contributes to drug and therapy innovation, allowing personalized treatment plans for individual patients [82]. In the digital marketing context, AI is invaluable because it enhances the precision of targeted advertising, elevates customer experiences, and predicts consumer behavior [83], [84].

In the context of tactical autonomy, the potential roles of AI in HAT become even more critical. Tactical autonomy refers to the ability of autonomous systems to make decisions and take action in real-time, often in complex and unpredictable environments [12]. AI-powered systems can provide soldiers with real-time battlefield information and can also be used to develop autonomous weapons systems that can operate without human intervention [12]. The potential benefits of AI in tactical autonomy are significant. AI systems can help improve situational awareness, identify and track targets, plan and execute missions, communicate with other systems, and make decisions. This can lead to increased safety, efficiency, and effectiveness in military operations [24], [85].

**Provide situational awareness.** As explained above, AI systems can collect, process, and analyze large amounts of data from sensors, cameras, and other sources to provide humans with an enhanced understanding of complex and dynamic environments [86]. It offers real-time insights, predictions, and suggestions that help human operators make informed decisions. This can help humans make better decisions and take appropriate actions.

**Plan and execute missions**. AI systems can plan and execute missions considering various factors, such as the team environment, capabilities, and risks. This allows human operators to make high-level decisions and manage the overall mission.

**Communicate with other systems.** AI systems can communicate with other systems, such as other autonomous vehicles and command and control centers. This will help ensure that the team works effectively together.

**Learn and adapt**. AI systems can learn from experience and adapt their behavior accordingly. This allows them to become more effective over time.

**Make decisions**. AI systems can make decisions that are enhanced even in complex and uncertain situations. This can help humans avoid making mistakes and ensure that the team always acts in the best interests.

However, some challenges must be addressed. One challenge is to ensure that AI systems are reliable and safe. Another challenge is the need to develop trust between humans



Fig. 2: Situation models for HAT [56].

and AI systems. Finally, there are ethical considerations that must be considered, such as the potential for AI systems to be used for malicious purposes. Despite these challenges, AI can revolutionize tactical autonomy. As AI systems continue to develop, we expect to see even more innovative and effective applications of AI in this area.

# IX. HUMAN-AI INTERACTION IN HAT FOR TACTICAL AUTONOMY

Effective human-AI interaction is crucial for successful HAT implementation. HAT systems are designed to allow human and autonomous systems to work together effectively in complex and dynamic environments. Section VIII explored how AI empowers HAT systems, particularly tactical operations. However, to harness the full potential of AI and collaborate effectively, well-designed user interfaces are essential. This section explores the key factors and Human-Machine Interface (HMI) design principles to consider when designing HAT interfaces, ultimately ensuring seamless human-machine collaboration. For example:

**Transparency and Explainability**. These principles are fundamental to ensure that human operators can understand, trust, and effectively collaborate with autonomous systems [6], [87]. Transparency refers to the extent to which the human operator can understand how an autonomous system works and why it makes the decisions it does [6], [88]. In the context of HAT interfaces, transparency involves providing operators with insights into the functioning of an autonomous system and making decisions [71]. In contrast, explainability refers to the extent to which a human operator can understand the rationale behind an autonomous system's decisions [89], [90]. Achieving real-time transparency and explainability in HAT interfaces is important for human operators to rely on AI-driven recommendations and actions. However, achieving explainability and transparency in human-AI interaction within the context of tactical autonomy settings requires several advanced strategies and technologies [91].

**Context Awareness.** HAT interfaces should provide human operators with the status of autonomous agents, the overall mission, and a clear and real-time understanding of the underlying tactical environment [92], [93]. Based on the current task and context, displaying relevant real-time

information about the tactical environment, such as maps, sensor data, and mission objectives, is important to enhance human operators' situational awareness [94], [95].

Adaptability and Flexibility. Tactical autonomy settings are often characterized by rapidly changing conditions. HAT systems are designed to operate in dynamic and unpredictable environments where the conditions can change rapidly. Therefore, the human-AI interaction mechanism must be able to adapt to these changes and be sufficiently flexible to accommodate various tasks, goals, and environments [96]. An adaptable HAI system can adjust its behavior, decision-making processes, and responses to accommodate these changes [97]. This allows the system to remain effective and relevant in a constantly evolving context.

**Safety and Redundancy**. These aspects help improve the reliability, robustness, and trustworthiness of HAT systems in dynamic and potentially dangerous environments [98], [99]. Safety refers to measures and mechanisms implemented to prevent accidents, mitigate risks, and ensure that the system operates without harming humans, property, or the mission. Redundancy, on the other hand, involves duplicating critical components or functions within the HAT system to ensure that backups are available in case of failure [100]. The work in [101] provides an overview of the current state of safety solutions and challenges in ensuring the safety of autonomous systems.

Shared Mental Model. Developing shared mental models between humans and autonomous systems is important for effective collaboration and communication [102], [103]. A shared mental model refers to a common understanding of the task, environment, and capabilities of humans and autonomous systems [58], [104]. To promote the development of shared mental models and strengthen the collaboration between humans and autonomous systems, several critical strategies should be implemented [55]. First, clear communication is very important. This involves using a common language or terminology that is understandable to humans and autonomous systems. Second, feedback mechanisms play a significant role. Providing humans with feedback on the performance of autonomous systems enhances understanding and trust [55]. Third, visualization tools are also equally important. They help humans understand the internal states and reasoning processes of autonomous systems. Finally, designing a human-autonomy system user interface and interaction mechanisms to facilitate effective communication and collaboration is important [55], [105].

# X. OPPORTUNITIES AND CHALLENGES

Moving from design principles to practical applications requires careful consideration of the broader landscape. This section explores the opportunities and challenges associated with using AI to enhance HAT in tactical autonomy.

### A. Opportunities of HAT in Tactical Autonomy

HAT is a promising technology with the potential to improve the safety and effectiveness of military mission-critical operations [106]. As discussed above, HAT is a concept that focuses on the collaboration and interaction between humans and autonomous systems or AI-driven technologies, particularly in scenarios where both entities work together toward a common goal [17]. This concept presents numerous opportunities across various domains. It is particularly important in the context of tactical autonomy and in defense and military areas for several compelling opportunities:

**Enhanced Decision-making**. Autonomous systems powered by AI can analyze vast amounts of data rapidly, providing human operators with real-time, data-driven insights to make more informed and effective decisions.

**Enhanced performance**. HAT can significantly enhance overall performance by leveraging the strengths of humans and intelligent autonomous systems [3], [107], [108]. Humans possess cognitive abilities such as creativity, intuition, and complex decision-making, whereas autonomous systems provide computational power, precision, and efficiency.

**Increased efficiency**. HAT systems can help reduce the risk of human error by automating tasks that are prone to human error. This can lead to safer operations, fewer accidents, and improved efficiency [3], [109]. In addition to this, HAT systems can help human operators focus on more important tasks. For example, in the aviation industry, HAT systems can automate tasks such as aircraft system monitoring and navigation. This allows the human pilot to focus on critical tasks such as decision-making and communication with air traffic control [110].

**Improved safety**. HAT systems can help improve safety by automating complex tasks that are extremely difficult for humans to perform [3]. For example, autonomous systems can be used to perform difficult tasks or pose risks to humans, such as driving vehicles under hazardous conditions. Autonomous systems can also be programmed to follow safety procedures more consistently than humans, and they can be equipped with sensors that detect hazards that humans may not be able to detect.

**Risk reduction**. By integrating intelligent autonomous system agents, human team members can delegate high-risk tasks to

autonomous agents, which mitigates risks and improves overall safety in dynamic and complex environments [109].

**Enhanced Capabilities.** HAT can help enhance the capabilities of human operators by providing them with access to information and resources that they would not otherwise have [111]. This can help them make better decisions and take more effective actions.

Adaptability and Flexibility. HAT systems should be flexible and adaptable to dynamic environments. Both humans and autonomous systems should adjust their behaviors and decision-making in response to evolving situations. Autonomous systems can adapt to dynamic and changing environments more rapidly than humans [3], [112]. Their ability to process real-time data and adjust their actions accordingly enhances the team's overall adaptability and resilience.

### B. HAT Challenges in Tactical Operations

While HAT offers significant opportunities, it also presents critical challenges that must be addressed for successful implementation. Here, we present some key challenges associated with HAT for tactical autonomy:

**Trust**. Investigating the factors that influence human trust in AI systems and developing strategies to enhance trust between humans and AI is crucial. Trust is critical for effective collaboration and decision-making in human-autonomy teams because humans must be confident that AI systems will behave safely and predictably. Therefore, AI systems should be designed to be transparent and explainable so that humans can understand how they make decisions. For example, the authors in [113] emphasize the importance of exploring trust dynamics within human-autonomy teams. They suggest a need for a detailed and qualitative analysis of team processes to understand how trust can be established or eroded over time. Such insights can contribute to more refined human-autonomy team designs and guide the development of autonomous agents that prioritize the element of trust.

Reliability. It is important to ensure that AI-powered autonomous systems are reliable [58]. Although HAT offers several potential benefits, ensuring the reliability and trustworthiness of these systems is essential for maintaining safety, ethical standards, and public confidence [58]. In the context of this study, trustworthiness refers to how well an autonomous agent earns the trust of other agents in the team, including humans and other autonomous agents. Trustworthiness is important because it allows humans to trust autonomous agents to operate safely and reliably. One of the key challenges in HAT is ensuring that humans and autonomous systems can trust and cooperate. This is especially important in complex and dynamic environments, where human and autonomous systems must be able to make quick decisions and adapt to changing conditions. Researchers must develop methods for improving the transparency and explainability of autonomous systems and methods for training humans to better understand and work with autonomous systems.

Lack of Transparency and Explainability of AI. Ensuring real-time transparency and explainability is crucial for building trust and enhancing situational awareness in AI systems [114], [115]. Human understanding of autonomous system decision-making is essential for effective collaboration, particularly in situations with significant consequences such as self-driving cars or autonomous weapons systems. However, designing transparent algorithms and interfaces to interpret autonomous system actions is a complex challenge.

**Human-machine Collaboration**. It is important to ensure that humans and autonomous systems can effectively work together. This requires careful design of the HAT system, and training for both humans and autonomous systems. Hence, the need for better human-machine interfaces that allow humans and machines to work together effectively is a critical challenge.

**Shared Situational Awareness**. Effective collaboration between humans and intelligent autonomous system agents requires maintaining shared situational awareness among the team members [67]. However, the critical challenge lies in designing and ensuring that all members have access to relevant information and can interpret and understand it consistently. Therefore, shared situational awareness in HAT is critical for human agents. This is because human agents can be overwhelmed by the information provided by autonomous systems. Processing a large amount of information while making critical decisions can lead to cognitive overload in human agents, and human agents may also need to be trained to effectively use tools and interfaces that facilitate shared situational awareness.

**Workload Distribution**. Allocating workloads appropriately between humans and autonomous systems is crucial to prevent cognitive overload or underutilization of computing resources. Achieving a balance that optimizes the strengths of both team members and guarantees efficient task execution is a critical challenge, particularly in complex and dynamic environments.

Ethical Implications. HAT raises several ethical implications, such as the potential for autonomous systems can make decisions that result in harm to humans. As HAT systems become more sophisticated, it is important to consider ethical implications carefully prior to deploying HAT systems. For example, how can we ensure that HAT systems are used safely and responsibly not to harm humans (either intentionally or unintentionally)? How can we prevent HAT systems from being used for malicious purposes? How can we ensure that HAT systems are used in a fair and just manner? Researchers should work with policymakers and ethicists to develop ethical guidelines for the development and use of HAT systems.

# C. Decision Logic of Autonomous Agents

Understanding the decision logic of autonomous agents is essential for ensuring safe and effective collaboration between humans and intelligent autonomous systems.

**Black-box Models**. Many autonomous systems use black-box models, which are ML models that are trained on large

amounts of data, where the relationships between the inputs and outputs of the models are complex and nonlinear. In the HAT context, black-box models can be used to control autonomous systems in various ways [116]. For example, a black-box model can be used to control the navigation of autonomous vehicles or the weapons system of autonomous robots. However, using black-box models in HAT poses several challenges. One challenge is that it can be difficult for humans to understand how autonomous systems are making decisions [117]. This can lead to a lack of trust in autonomous systems and make it difficult for humans to collaborate effectively with them.

**High-dimensionality of Data**. Autonomous systems often process large amounts of high-dimensional data. This can make it difficult for humans to visualize data and understand the factors that influence an autonomous system's decisions [118]. When data are high-dimensional, this means that different features (variables) that are being measured [119]. In the HAT context, high-dimensional data can make it difficult for humans to understand how autonomous systems make decisions. This challenge pertains to the complexity and volume of data that autonomous systems generate and use, and it can impact various aspects of HAT, including decision-making, situational awareness, and communication between team members.

Uncertainty of Data. Autonomous systems often operate in uncertain environments. This can make it difficult for humans to determine the reliability of autonomous system decisions. Uncertainty of data is a significant challenge in HAT and can impact the effectiveness, safety, and trustworthiness of human-autonomy systems. In HAT, uncertainty can arise from various sources and manifest in different forms, including noisy or incomplete sensor data, environmental uncertainty, and human-automation interaction uncertainty [120]. The data may also be outdated or may not represent the current situation. In addition, the data may be biased or manipulated by an adversary. Several methods can be used to address the challenge of uncertainty in HAT data [121]. For example, it is important to use data that are as high quality as possible. It is also important to employ advanced techniques to detect and mitigate data uncertainty. Furthermore, it is important to design HAT systems that are robust against uncertainty.

**Unforeseen Biases.** Another critical challenge is the potential for unforeseen biases. AI systems are trained on data, and if the data are biased, the AI system will be biased as well. This could lead AI systems to make unfair or discriminatory decisions [122], [123]. It is important to carefully select the data on which AI systems are trained and to employ techniques to mitigate bias. Autonomous systems may be biased in ways that are not immediately obvious to humans. This can lead to autonomous systems making poor decisions.

Addressing these critical challenges in integrating and deploying HAT in AI-powered domains is essential to maximize benefits and ensure safe, ethical, and effective operation in complex and dynamic environments. Despite these challenges, we believe that the potential benefits of using AI in HAT are immense. By combining the strengths of humans and machines, AI can revolutionize military operations and make the world a safer place.

# D. Function Allocation Challenges in HAT

Function allocation refers to the distribution of tasks and responsibilities between humans and autonomous systems within a team [18]. Allocation is crucial for optimizing team performance, ensuring efficiency, and maintaining safety in complex operational environments. It determines how information is processed, integrated, and presented to human operators to deliver relevant and timely information that enhances situational awareness. This process includes considerations such as data fusion, visualization techniques, and feedback mechanisms from autonomous systems to humans [124]. Traditionally, function allocation has been based on what humans and machines are good at. However, this approach overlooks several important factors that must be addressed. A more comprehensive approach involves analyzing task demands, exploring task distribution strategies, examining the interdependence between humans and machines, and considering the associated trade-offs [18]. The work in [18] highlights several key considerations in function allocation that are particularly relevant in the era of human-autonomy teaming. Addressing these considerations can help human-autonomy teams leverage the strengths of both humans and machines, leading to improved performance, decision-making, and overall mission success in tactical operations. Some of these considerations relevant to this paper are discussed below.

**Cognitive Workload Distribution**. A crucial consideration is the distribution of cognitive workload between humans and intelligent autonomous systems. Repetitive tasks, rule-based tasks, or processes that involve the rapid processing of large amounts of data are often better suited for automation. Conversely, tasks requiring creativity, complex decision-making based on contextual understanding, or ethical considerations are generally more suitable for human operators.

Situational Awareness. Function allocation plays a critical role in shaping situational awareness in tactical operations, particularly when integrating AI into HAT. Situational awareness relies heavily on effective function allocation, which impacts the cognitive load experienced by human operators. By assigning tasks appropriately based on their complexity and cognitive demands, operators can enhance their ability to maintain situational awareness [94]. For example, automating routine and repetitive tasks allows human operators to focus on higher-level cognitive tasks that require situational understanding and decision-making [94]. Task allocation significantly influences the level of collaboration and interaction between humans and autonomous systems. Collaborative function allocation models, where humans and AI work together, can improve situational awareness by leveraging the strengths of both entities. This collaboration may involve shared decision-making, coordinated task execution, and continuous feedback loops [125].

Flexibility and Adaptability. The allocation of functions should be flexible and adaptable to changing circumstances, such as dynamic situational awareness in tactical environments [126]. Strategies for function allocation that prioritize adaptability and flexibility enable quick adjustments to task assignments and information flow. This adaptability ensures that situational awareness remains robust even in evolving scenarios or unexpected events. Human-autonomy teams operate in dynamic environments where tasks and priorities may shift. Therefore, systems must be designed with the ability to reassign tasks or transfer control seamlessly based on real-time conditions and input from both humans and machines.

**Transparency and Trust.** Clear communication and transparency in function allocation are essential for building trust within the team. Human operators should understand how tasks are distributed among humans and autonomous systems, including the criteria used for decision-making. Transparent allocation enhances trust, reduces uncertainty, and promotes effective collaboration.

Ethical and Legal Considerations. Function allocation must also consider ethical and legal implications. This includes ensuring that humans retain control over critical decisions, addressing potential biases in algorithmic decision-making, and adhering to regulatory frameworks governing autonomous systems in specific domains such as defense or healthcare.

# XI. PROPOSED FRAMEWORK FOR AI-DRIVEN HAT IN TACTICAL OPERATIONS

In this section, we present a comprehensive framework (Figure 3) for AI-driven HAT in tactical operations, and we provide a conceptual structure to enhance the integration of AI into these environments. By identifying and organizing key elements, this framework can guide future research and development. It comprises four main components: trust and transparency, function allocation, situational awareness, and ethical considerations, each representing a critical aspect of AI-driven HAT that requires further exploration. By providing a structured approach, the proposed framework facilitates a systematic investigation of the challenges and opportunities associated with AI-driven HAT for tactical operations. We include comparative insights, new examples, and potential real-world implementation strategies to illustrate how our work advances beyond the existing literature. Future research is needed to develop, implement, and validate these concepts in real-world settings.

# A. Trust and Transparency

**Explainable AI Models.** XAI models are crucial to ensure that human operators can understand AI decisions, particularly in time-sensitive environments. For example, in military drone operations, a tactical XAI model can provide real-time explanations for target identification using visual overlays to highlight specific features and auditory alerts to convey urgency. The proposed framework introduces a tactical XAI system that is tailored to the demands of such



Fig. 3: Proposed Framework for AI-Driven HAT in Tactical Operations

environments, thereby providing concise, actionable insights during mission-critical moments. It envisions a multi-modal explanation system that employs visual, auditory, and tactile cues to communicate AI reasoning without overwhelming the operator's cognitive load. In addition, an adaptive explanation component adjusts the depth and complexity of the information based on the operator's expertise and cognitive state, providing flexible levels of detail according to operational needs and time constraints.

**Trust Calibration Mechanisms.** In HAT systems, trust calibration must be adaptive rather than static to respond to evolving tactical scenarios. Drawing inspiration from reinforcement learning techniques, the proposed framework introduces a dynamic trust calibration system that adjusts AI autonomy based on operator behavior, AI performance, and mission criticality. In this system, trust levels are continuously recalibrated through real-time feedback to assess factors such as behavioral cues, physiological signals, and direct operator inputs. For example, in time-sensitive missions like search-and-rescue, if the AI system consistently performs with high accuracy, its autonomy is increased, which minimizes

the need for human verification. Conversely, if the AI system misclassifies targets or poses risks, trust levels decrease, which increases human oversight. By autonomously adapting to operator inputs, mission outcomes, and evolving conditions, the underlying system enables seamless human-AI collaboration, enhancing decision-making through continuous real-time feedback and adjustments. This adaptive trust mechanism helps human operators remain confident in AI decisions, leading to better teamwork, especially during critical missions.

# B. Function Allocation

**Dynamic Task Distribution and Adaptability**. Existing function allocation in HAT systems is primarily static and often fails to accommodate changing tactical conditions. To address this limitation, the proposed framework employs adaptive algorithms capable of dynamically distributing tasks based on variables, such as operator cognitive load, stress indicators, and mission requirements. The proposed framework emphasizes the importance of context-aware algorithms that modify task allocation in real-time, considering factors

such as operator cognitive state, stress levels, and mission complexity. By considering variables such as mission type, environmental conditions, and operational data, these adaptive algorithms can optimize the distribution of responsibilities between humans and AI, ensuring that task allocation remains responsive to evolving tactical situations. Achieving this level of adaptability requires AI-driven HAT systems to be designed with flexibility as a core feature. AI architectures should be capable of rapid reconfiguration in response to new inputs, enabling them to adjust to shifting mission objectives, environmental changes, and variations in operator states. For example, reinforcement learning models can be employed to adapt task strategies based on real-time feedback, continuously optimizing system performance under changing conditions. Furthermore, incorporating modular AI components, such as plug-and-play sensors and dynamic data processing units, facilitates rapid updates, which ensures the system's resilience against unforeseen changes. This approach not only enhances AI efficiency but also guarantees better alignment with operators' immediate needs, thereby improving overall mission success rates and operator trust. For example, complex tasks like real-time threat assessment, can be assigned to AI systems during high-stress scenarios, whereas decision-making regarding ethical dilemmas, such as potential civilian casualties, remains the responsibility of human operators.

Cognitive Load Optimization. In traditional HAT systems, the cognitive load of human operators is often either underestimated or ignored, leading to reduced performance and potential mission failures. Our framework proposes an adaptive cognitive load-balancing model that dynamically adjusts task complexity, presentation, and pace based on real-time operator states [127]. By aligning task demands with operator skills, the proposed approach considers individual strengths, weaknesses, and preferences, thereby allowing for a gradual increase in challenges to promote skill development. For example, during joint reconnaissance missions, tasks requiring high situational awareness can be assigned to experienced operators, and routine data entry is managed by AI. This adaptive approach ensures that operators are not overwhelmed and facilitates effective decision-making in tactical environments.

# C. Situational Awareness

**AI-Enhanced Perception**. Traditional situational awareness models in HAT systems often rely on limited or isolated data streams, which results in incomplete or biased situational models. Our framework attempts to overcome these limitations by implementing AI-enhanced perception that integrates diverse data sources, such as radar, satellite imagery, and ground sensors, to create a more holistic and accurate situational model [128]. The proposed approach leverages multi-sensor fusion techniques, including Bayesian inference, convolutional neural networks for image analysis, and Kalman filtering for real-time sensor data processing, to combine data into coherent and interpretable representations. By merging various sensory inputs, the model maintains consistency and reliability in situational awareness, facilitating seamless communication between AI and human operators. To further enhance real-time situational awareness, the framework incorporates advanced analytics tools that continuously update the situational model, identify emerging threats, and provide timely alerts to operators. This real-time processing capability ensures that sudden changes, such as enemy movements or environmental shifts, are detected and communicated clearly and promptly. In addition, AI-enhanced perception can identify and highlight anomalous patterns that human operators might otherwise overlook, particularly in dynamic tactical environments. For example, in an urban combat simulation, this integration allows AI to identify potential threats overlooked by human operators, thereby offering recommendations that improve decision accuracy and reduce response times. By maintaining an up-to-date, comprehensive situational awareness, the proposed framework can improve decision-making accuracy and enhance the operational readiness of HAT systems.

Shared Mental Models. In tactical operations, achieving a shared mental model between human operators and AI is important [81]. For example, during a coordinated air-ground mission, an AI system can continuously update its situational assessment and communicate key changes to the human team members, ensuring that both AI and humans have an aligned understanding of the mission's progress. Our framework proposes a concept for dynamic shared cognition that can align AI and human understanding in tactical situations to enhance team cohesion and decision-making. This theoretical approach introduces potential mechanisms for comparing and assessing differences between AI and human situational assessments. The concept further outlines possibilities for cognitive synchronization through targeted information exchange to address potential discrepancies in situation understanding.

# D. Ethical Considerations

Ethical Decision Support. Ethical decision-making in HAT systems typically involves predefined rules or rigid moral frameworks, which limit their adaptability to dynamic tactical situations. In tactical situations, AI-driven HAT can offer proactive ethical decision support by helping human operators navigate legal, moral, and operational implications. For example, during a peacekeeping mission simulation, AI could propose nonlethal measures to de-escalate a conflict while also presenting operators with clear explanations of the ethical implications of each choice. This ensures ethical compliance while enabling informed decision-making. The proposed framework introduces adaptive ethical decision models that integrate ethical guidelines with real-time decision-making processes. These models assess the ethical implications of potential actions and provide human operators with options aligned with international laws and moral standards. Future research should therefore focus on embedding real-time ethical reasoning algorithms that ensure compliance with international laws and offer moral decision support, particularly during conflict situations.

Accountability Frameworks. The proposed accountability framework clearly defines distributed responsibilities between AI and human team members. This theoretical model introduces possibilities for analyzing team decisions and actions after they occur, allowing for thorough review and assessment. This concept presents potential approaches for tracking and documenting the contributions of AI and human team members to significant operational decisions.

### XII. PRACTICAL RECOMMENDATIONS

In addition to proposing a comprehensive framework (Section XI), this study provides practical recommendations that can contribute to the implementation of AI-driven HAT systems in tactical environments. After exploring the opportunities and challenges of AI-driven HAT for tactical autonomy (Section X), this section provides clear guidance for policymakers, practitioners, and researchers regarding the complexities of HAT development and implementation.

**Develop Transparent and XAI Systems**. Developing transparent and explainable AI systems is important for building trust between human operators and AI teammates. Interpretable machine learning algorithms can improve the explainability of AI systems [129]. Implementing XAI techniques such as generating visualizations or context-based explanations to make AI decision-making processes more transparent, is an example of an actionable step. This empowers human operators to understand the rationale behind AI recommendations and promotes informed collaborative decision-making [130]. We recommend implementing XAI models that offer visual, auditory, and textual explanations of AI decisions. These models should be tailored to the tactical environment, such as overlaying battlefield maps with AI-generated insights to assist operators in decision-making.

**Building Robust AI for Uncertainty**. Given the dynamic and unpredictable nature of tactical environments, AI systems should be trained on diverse real-world datasets reflecting various scenarios [131]. This training enhances the system's ability to handle uncertainty and make context-appropriate decisions. Prioritizing robustness against uncertainty and ambiguity ensures that AI systems can effectively adapt to dynamic operational settings. This enables AI systems to make context-appropriate decisions even in unforeseen circumstances.

**Human-AI Collaboration**. Effective Human-AI collaboration in tactical autonomy requires a symbiotic relationship between human decision-making and AI assistance. Instead of deploying fully autonomous systems, AI tools should be designed to provide recommendations and options that support human operators, enabling them to make informed decisions while leveraging AI's analytical capabilities. To achieve this, it is important to emphasize human-centric design throughout the development of HAT systems. This approach involves an iterative design process that actively incorporates user feedback at every stage, from conceptual prototyping to field testing. By engaging operators in this process, developers can ensure that AI systems closely align with user needs, thereby enhancing both usability and operator trust. For example, user-centered design frameworks, such as participatory design and co-design workshops, can be employed to gather input directly from operators, allowing AI systems to be tailored to specific operational contexts and user requirements. Training programs for operators are also critical because they help users understand AI's capabilities and limitations, providing more effective collaboration in tactical environments. The iterative development process should include usability testing, interface adjustments, and continuous model training based on real-world interactions. By focusing on human-centric design and continuous user engagement, AI systems can become more intuitive, reduce cognitive load, and facilitate smooth decision-making processes, thereby improving the overall effectiveness of HAT operations.

**Emphasize Human-AI Training and Education**. Policymakers and practitioners must invest in developing a comprehensive training program to familiarize human operators with AI functionalities and limitations. Designing training programs that cover the full potential of AI capabilities, limitations, and best practices for collaboration in tactical operations is important. Using simulation-based training to allow operators to practice in a safe and controlled environment and understand best practices for collaborating with AI systems during tactical operations can be effective.

**Cybersecurity and Privacy**. Robust cybersecurity measures and data privacy considerations are essential for secure and ethical HAT operations. Policymakers must address cybersecurity concerns by implementing end-to-end encryption for communication among AI-assisted tactical teams. This protects mission-critical information from potential adversaries. In addition, policymakers should examine existing legal and regulatory frameworks, such as the General Data Protection Regulation (GDPR), governing HAT to ensure that they address data privacy concerns [132].

Continuous Trust Assessment Mechanisms. Implementing continuous trust assessment mechanisms is important for maintaining operator confidence in AI systems and ensuring effective collaboration. To achieve this, user feedback should be systematically integrated into AI systems by creating feedback loops that allow operators to provide real-time evaluations of AI decisions. For example, real-time feedback interfaces can enable operators to rate AI decisions on reliability, which can be used to dynamically adjust trust levels based on user responses [58]. Trust calibration algorithms also play an important role in evaluating and adjusting trust levels. These algorithms can monitor operator behavior and performance metrics to adjust AI autonomy levels in real-time [133]. Additionally, physiological monitoring tools, such as sensors for heart rate variability, can be used to assess trust indirectly during interactions with AI systems [127]. In addition, existing trust measurement frameworks, as discussed in [134], offer methods to quantitatively assess trust in automated systems during HAT operations. These frameworks provide empirical insights into operator trust levels by generating real-time reports that help inform adjustments to AI behaviors, thereby fostering more effective human-AI collaboration.

**Implement Protocols for System Failures and Recovery.** Designing AI systems with fail-safe mechanisms and establishing protocols that allow human operators to regain control in the event of system failures is critical. Human operators must intervene and take control when necessary to ensure operational continuity and safety in dynamic environments.

AI Training for Real-World Scenarios. Training AI systems using real-world data from tactical operations is important for ensuring accurate, context-aware decision-making. In particular, AI systems should be trained using datasets that simulate realistic operational contexts. For example, using datasets like the DARPA's OFFensive Swarm-Enabled Tactics (OFFSET) [135] or the Military Operations on Urban Terrain (MOUT) [136] simulation data can significantly enhance AI adaptability in combat situations by replicating battlefield dynamics. Similarly, datasets such as the FEMA dataset<sup>1</sup> on disaster response can prepare AI systems for handling natural or human-made disaster scenarios, improving their capacity for context-specific decision-making. To optimize learning, AI models should incorporate advanced techniques such as reinforcement learning and domain adaptation. Reinforcement learning allows AI systems to interact with simulated environments, enabling them to adapt behaviors based on trial-and-error feedback and learn optimal responses [131]. Furthermore, domain adaptation can help AI systems generalize from training data to real-world deployment by learning from pre-existing datasets and adapting to new operational environments [137]. This approach ensures that AI systems can effectively manage unexpected variables commonly encountered in tactical settings.

Develop Ethics and Regulations. Policymakers and AI researchers must collaborate to establish ethical guidelines and legal frameworks for the use of AI in tactical autonomy. These guidelines should address transparency, accountability, AI bias, and the rights of human operators within human-autonomy teams to ensure the safe, ethical, and responsible deployment of autonomous systems. To achieve this, ethical decision support should be seamlessly integrated into HAT systems, providing operators with real-time ethical guidance and decision options based on international laws and mission rules, even in rapidly evolving scenarios. Ethical decision support modules should be designed to help human operators make legally compliant and morally sound decisions during tactical operations [111]. These modules can leverage decision trees or rule-based AI systems that embed ethical principles and offer real-time recommendations aligned with international humanitarian laws, such as promoting non-lethal engagement in conflict zones. Drawing from frameworks like Asimov's laws of robotics [138], [139], extended to incorporate modern ethical guidelines for military and emergency operations, these

modules present clear decision options that align with mission objectives while adhering to established ethical norms. To further ensure ethical compliance, HAT systems should include compliance-checking mechanisms that continuously monitor AI decisions against legal standards [140]. Real-time compliance checks can flag actions that may violate ethical guidelines, prompting human operators to review and, if necessary, override AI-generated decisions. These compliance checks can be implemented using rule-based AI systems that reference legal databases in real-time, ensuring that all AI decisions undergo thorough verification before execution. Integrating ethical decision support with compliance monitoring promotes informed decision-making and ensures awareness of legal or ethical risks, thus enabling safe and responsible AI deployment in high-stakes environments [140].

Pilot Programs and Cross-Disciplinary Collaborations. We recommend launching pilot programs that involve a collaborative effort between military agencies, emergency response teams, academic research centers, and technology companies. These pilot programs should focus on testing and refining the proposed AI-driven HAT systems in controlled yet realistic environments. Effective implementation requires cross-disciplinary teams that include AI researchers, human factor experts, ethicists, legal professionals, and tactical operators. By bringing together these diverse perspectives, pilot programs can address the complex challenges of HAT development, such as ethical decision-making, operator trust, and system reliability, thus ensuring that theoretical frameworks are practically applicable. Pilot sites and testing environments should be carefully identified to enhance the impact of these collaborations. Military training centers and disaster response simulation facilities offer controlled settings that replicate real-world scenarios, providing researchers with safe spaces to validate AI performance and identify areas for refinement before broader deployment. Developing clear evaluation criteria and metrics is important for assessing the effectiveness of AI-driven HAT systems during pilot tests. Metrics such as task completion rates, human-operator feedback, and compliance with legal standards can help determine system readiness for real-world applications. By adopting an iterative approach, the collaborations can ensure that the models are not only theoretically sound but also adaptable to real-world conditions, allowing continuous refinement based on pilot outcomes. This approach bridges the gap between theoretical frameworks and practical implementations and contributes to the development of reliable, ethical, and effective HAT systems that satisfy the complex demands of tactical operations.

# XIII. CONCLUSION

This paper has explored the realm of AI-driven human-autonomy collaboration within tactical operations, demonstrating how this integration represents a paradigm shift in decision-making, situational awareness, and operational efficiency. Through our proposed framework, we have provided a structured approach to understanding and advancing AI-driven HAT, organizing key components into four critical areas: trust and transparency, function allocation, situational awareness, and ethical considerations. This framework serves as a foundation for future research and development, offering a systematic way to address the complex challenges of integrating AI into tactical operations. Our exploration of the opportunities and challenges in this domain highlights the transformative potential of AI-driven HAT across diverse sectors, including military operations, emergency response, and law enforcement. The integration of AI technologies offers significant advantages while demanding careful consideration of critical factors, such as trust, transparency, and cognitive load management. Looking forward, it is important to chart a path that embraces the ethical deployment of AI, establishes robust mechanisms for human oversight, and promotes interdisciplinary collaboration among AI researchers, human factor experts, and domain specialists. By addressing these critical challenges and leveraging these opportunities within the proposed framework, we envision a future where AI-powered HAT systems seamlessly integrate human intuition, ethical reasoning, and autonomous capabilities to achieve unprecedented levels of effectiveness in complex tactical environments.

This paper emphasizes the ongoing need for research and development efforts that prioritize human-centric design, transparency, and the establishment of a foundation where AI can serve as an empowering force in tactical autonomy. The proposed framework provides a structured approach for addressing these needs and guiding future developments. In our future work, we aim to investigate approaches for developing and validating scalable HAT systems that address the primary research challenges and knowledge gaps identified in this paper. The proposed system leverages state-of-the-art AI techniques to facilitate seamless collaboration, communication, and coordination between human operators and autonomous systems, emphasizing trust-building, explainability, and cognitive load management.

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