Trustworthiness in Multi-Agent UAV Systems: A Scoping Review

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Abstract

The integration of artificial intelligence (AI) into multi-unmanned aerial vehicle-assisted communication plays a pivotal role in sixth-generation wireless communication and beyond. Most AI techniques have primarily focused on AI-based applications and technical problems, rather than examining the accountability and trustworthiness of AI models, a crucial evaluation criteria for AI human beings. This work aims to provide a scoping review of the trustworthiness of AI in multi-agent UAV systems. Firstly, we present the background of multi-agent systems and methods to evaluate, enhance the trustworthiness of AI systems. Secondly, we review innovative techniques that address trustworthy requirements in terms of safety, robustness, privacy, accountability, explainability, and fairness, along with challenges in multi-agent UAV communications. Finally, we highlight several promising solutions and future research directions.

Keywords: Artificial Intelligence (AI), Multi-Agent Unnamed Aerial Vehicle (Multi-agent UAV), Trustworthiness.

1. Introduction

Multi-agent unmanned aerial vehicle (UAV) systems have recently gained significant attention in various real-time applications, such as monitoring applications, and transportation, industry, and communication Kurunathan et al. (2024). One of the critical challenges in UAV systems is how to establish and maintain cooperation, coordination, and communication among multiple UAVs autonomously to achieve overall objectives Bai et al. (2023).

In recent years, artificial intelligence/machine learning (AI/ML) has achieved many successes in various disciplines, such as smart cities, smart transport, healthcare, weather, and communication systems To et al. (2024); Kramar et al. (2024); Kurunathan et al. (2024). The increasing usage of AI and learning techniques has been demonstrated as key to designing intelligent and effective solutions, thanks to the responsibility to the dynamic and uncertain environment of multi-agent UAV systems Bai et al. (2023). AI techniques have significantly addressed various challenges, including diverse service requirements, higher quality-of-service demands, lower latency, and cost efficiency constraints to resources, energy, and data limitations, thereby improving the quality of applications and services Zuo et al. (2023). Moreover, multi-agent systems enable communication between agents across the entire network, accelerating learning and optimizing decision-making under the hetero-

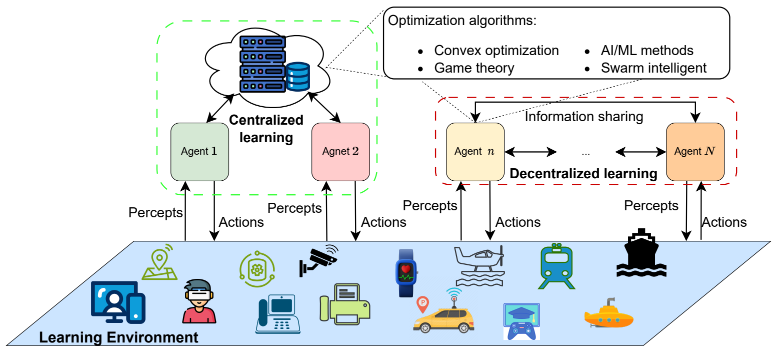

Figure 1: Multi-agent systems.

geneous communication systems Bai et al. (2023). Many works have investigated intelligent learning approaches to address the complex applications in UAV swarms such as trajectory planning, resource allocation, quality-of-service requirements, and communication coverage that the traditional methods are difficult to address due to the network's dynamic and distributed nature Bai et al. (2023); He et al. (2024); Sun et al. (2024).

However, this rapid development of new services and applications has also raised many concerns, including intelligent malicious attacks, data privacy issues, or unexpected system behaviors due to complexity in decision-making, black-box nature, and dynamic nature He et al. (2024); Sun et al. (2024). Specifically, when the number of agents increases significantly leading to increasing the complexity of developing trustworthy multi-agent systems. Therefore, trustworthiness is the foundational requirement to develop, deploy, and use AI solutions, which is not only for individual policies but also for group policies. Trustworthy AI refers to AI systems that are designed and developed to be safe, robust, generalizable, and capable of learning under ethical constraints Zhou et al. (2024b); Steen et al. (2023). Moreover, it requires that AI systems adhere to principles, guidelines, standardization, and management processes to ensure function safely and fairly. Therefore, this work aims to provide a short overview of recent works on the trustworthiness of intelligent UAV agents, focusing on aspects of safety, robustness, privacy, accountability, explainability, and fairness.

2. Background

In this section, we present firstly components including agent, organization, algorithm, and communication in multi-agent systems (MAS). In addition, state-of-the-art trustworthiness methods that evaluate the transparency of multi-agent methods are introduced.

2.1. Multi-Agent Systems

In a multi-agent system, each UAV (*i.e.*, drone) is considered as an agent and acts as a distributed module that works together through collaboration and communication to speed up the processing time, solve complex problems by collaborating or partitioning tasks reducing the operational costs, and achieve shared goals, offering scalability and adaptability Bousetouane (2025); Tran et al. (2025). The architecture of MAS is illustrated as Figure 1.

Agent: It is an intelligent entity that interacts with the system environment to gather, process data, and cooperate with its neighbors to generate the best policy/action achieving maximum its cumulative reward and common system goals Bousetouane (2025).

Organization: Organization refers to how agents work together for a shared purpose. The organization is categorized into centralized where agents send information to a control center that has the monopoly on making decisions, and decentralized, where agents communicate directly and share information to collectively solve problems Le et al. (2024).

Algorithm in MAS: Various optimization methods have been proposed to generate decision outputs including global optimization, game-theoretic approaches, AI/ML-based approaches, and heuristic and swarm intelligence approaches Hoang et al. (2024); Puente-Castro et al. (2022). These methods have addressed critical challenges in robotics, intelligent transport networks, healthcare, smart cities, and communication Rizk et al. (2018).

Communications: Effective communications between all agents in MAS are crucial for ensuring system operations. Moreover, the channel quality such as bandwidth, frequency, and the amount of information must be considered to avoid collision and loss of information at receivers side and reduce the communication delay, energy consumption, and communication overhead Maldonado et al. (2024).

2.2. Trustworthiness Methods

Evaluating the transparency of AI models can enhance trustworthiness, which is essential for building reliable autonomous decision systems in MAS. Generally, AI models are treated as black-box due to opaque and complicated to understand. In addition, as the number of agents increases, decision-making interactions become more complex and difficult to understand and explain impacting on the reliability and trustworthiness in AI systems Ramchurn et al. (2004). Consequently, trustworthy AI has been attracting attention from both government and scientific communities to ensure safe and trusted AI systems Nguyen et al. (2024). Various works have proposed different approaches to establishing trust in AI systems, adhering to guidelines on lawfulness, ethics, and robustness Kaur et al. (2022).

Different perspectives on trustworthy AI have been explored and evaluated in recent years. Several methods focused on the design phase which clearly defines trustworthy requirements and expectations for AI systems Commission et al. (2019). Other approaches are conducted by processing data input such as data privacy, detecting and defending data poisoning, pre-processing phases as dimensionality reduction, and data labeling making data fair, and diverse Zhou et al. (2024b). The modeling phase has also been studied providing explainability and interoperability of AI models, preventing and mitigating bias Kaur et al. (2022). Additionally, other research works utilized proper auditing and testing solutions to ensure accountability, transparency, and compliance with legal standards. Researchers also proposed human involvement, in which the final decision is made by combining AI-generated outputs with human experiences Nguyen et al. (2024). Authors Yu et al. (2013) did survey on using game approaches to evaluate the trust in sharing knowledge between agents in MAS. On the other hand, to enhance communication efficiency, large language models (LLMs)-based semantic information extraction is introduced to improve communication efficiency Zhou et al. (2024a). The objective of all these approaches is to ensure trust without causing harm to users and to maintain the unbiased and fair nature of AI systems.

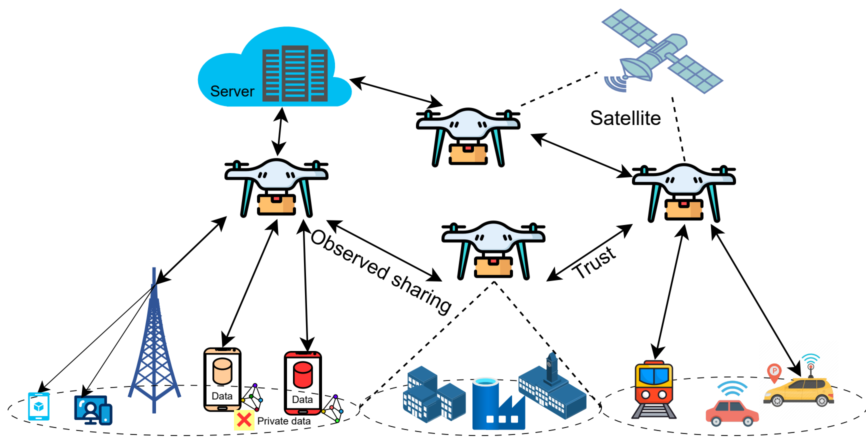

Figure 2: An overview of multi-agent UAV systems.

3. Trustworthiness in multi-agent UAV systems

In communication systems, UAVs are widely considered as flying access points or relay nodes to improve terrestrial communication and provide services like data collection and aerial computing, as shown in Figure 2. Unlike a single UAV, multiple UAVs will coordinate and cooperate to complete tasks in parallel, thereby reducing implementation time and communication overhead Ding et al. (2024). AI approaches such as reinforcement learning (RL), deep reinforcement learning (DRL), and deep learning (DL) demonstrated their remarkable ability to build intelligent multi-agent UAV systems in various applications, including energy harvesting, data sensing, network security, localization, and task offloading Kurunathan et al. (2024). However, there are considerable problems in UAV swarms *i.e.*, how to evaluate trust between UAVs and prevent harm when sharing observations between multiple UAVs due to the black-box nature and complexity in decision-making. In addition, the complexity of team policies also increases due to the increasing number of agents. As a result, it requires not only the trustworthiness of individual output but also the reliability of group interaction policies Zhou et al. (2024b). Therefore, investigating trustworthiness in intelligent multi-agent UAV systems is the key challenge for smart networks and services. Many works have focused on enforcing trustworthiness requirements in multi-agent UAV systems to provide a secure and reliable framework for delivering cutting-edge wireless services, as summarized in Table 1. In this section, we review trustworthiness features that have been investigated in recent works related to safety, robustness, privacy, accountability, explainability, and fairness in multi-agent UAV systems.

Safety refers to the development of safe MA learning models in which the action of one agent does not cause harm to the task or other agents involved Zhou et al. (2024b). Many approaches are addressing the safety of AI models such as adding constraints to the training process that encourage agents to avoid unsafe action Ma et al. (2024); Termehchi et al. (2024); Safaoui et al. (2024), authenticating the received learning message before integrating them into learning parameter updates Lv et al. (2024) or improve the safety by learning and teaching the dynamic and uncertainties of environment among agents in system Dey and Xu (2024).

Table 1: Summary of the literature on trustworthiness in multi-agent UAV systems.

Safety in multi-agent UAV systems			
Termehchi et al. (2024); Lv et al. (2024); Safaoui et al. (2024); Ma et al. (2024)			
Robustness in multi-agent UAV system			
Hazra et al. (2021); Chen et al. (2024); Islam et al. (2023); Wu et al. (2020)			
Learning with ethical constraints			
Privacy	Accountability	Explainability	Fairness
Le et al. (2024); He et al. (2024); Liu et al. (2024)	Wei et al. (2024); Bera et al. (2021); Senevirathna et al. (2024)	Guo (2020); Keneni et al. (2019); Patel et al. (2024); Haque et al. (2024)	Zhong et al. (2022); He et al. (2023); Tao et al. (2024)

Robustness refers to the ability of the system to maintain performance and stability despite uncertainties, and adversarial attacks Zhou et al. (2024b). Researchers have investigated many aspects of improving the performance of trained models with various challenges in real-world applications such as trigger and defense mechanisms for backdoor attack, jammer Islam et al. (2023); Wu et al. (2020), addressing the gap between simulation and reality of trained policy Chen et al. (2024). In MAS when one agent fails or one or more UAVs are knocked off the network, the system performs poorly. To address this problem, Hazra et al. (2021) utilized a biological network-based low-complexity algorithm to design a reliable multi-UAV network topology providing end-to-end services.

Privacy refers to protecting the sensitive data that is prohibited collected or shared by AI systems Senevirathna et al. (2024). To protect sensitive data when sharing information to a centralized server, Le et al. (2024) provided an overview of distributed learning as federated learning in multi-agent UAV systems. In that context, client sides only transfer trained model parameters to server sides (*e.g.*, UAVs) instead of sharing raw data in centralized learning, multiple UAVs collaborate to optimize their learning policy, thus supporting heterogeneous and delay-sensitive requirements. He et al. (2024); Liu et al. (2024) investigated blockchain-assisted decentralized learning alleviating computation burden, mitigating security threats, and building trusted collaboration framework among UAVs thanks to the transparency, tamper-proofing, and traceability blockchain features.

Accountability refers to the need to monitor AI decision-making methods that do not cause harm to users or society Senevirathna et al. (2024). It is vital to discover which root causes of damage in the system and how the system can autonomously detect and defend against harm. Attacks can occur in the collecting and processing data phase, during communication, observation sharing, or due to black-box problems of algorithms Senevirathna et al. (2024). To ensure secured data accessing and sharing among multiple UAVs, a trust AI-based decentralized anomaly detection framework using an ML-based data analytic method is introduced in Wei et al. (2024). Another aspect, a novel AI-envisioned blockchain-based security framework is proposed for secure communication in the internet of drones Bera et al. (2021). Methods based on explainable AI (XAI) methods have been investigated that enhance explainable and interpretable models also improve accountability in AI systems Senevirathna et al. (2024).

Explainability refers to the ability of intelligent models that produce understandable and interpretative explanations of their judgments and behaviors trusted by humans Senevirathna et al. (2024). Various XAI methods have been introduced to improve explainability such as symbolic representation, feature visualization, and local machine learning model reduction, neural network reduction Guo (2020). For instance, XAI is used in designated paths under various adverse conditions and enemies, using if-then rules to explain how routes are adjusted during implementation missions of UAVs Keneni et al. (2019). XAI-based methods are also used to improve the interpretability and transparency of the model's prediction that classified radio frequency jamming attacks Patel et al. (2024), and drones type enhancing the security of UAV networks Haque et al. (2024).

Fairness refers to a system generating outputs that do not depend on the priority of individuals or groups and discrimination Senevirathna et al. (2024). The fairness in multi-agent UAV systems can be investigated and optimized via power allocation issues, task offloading problems, service fairness, and so on Zhong et al. (2022); He et al. (2023); Tao et al. (2024). To ensure fairness between the strong users (*e.g.*, with higher channel gain) and weak users (*e.g.*, with lower channel gain) in the system, multiple access techniques like non-orthogonal multiple access, and rate splitting multiple access methods are applied using Zhong et al. (2022). In addition, authors proposed offloading and UAV selection approaches based on task size and the current state of UAVs to ensure fairness among UAVs and minimize energy consumption He et al. (2023).

Challenges: There are several challenges that multi-agent UAV systems will face in the future as (1) scalability: AI models should be responsible for large-scale system requirements, which will permit adaptation to system dynamics and heterogeneity; (2) generalization: the applicability of drone systems across various data modalities and application tasks; (3) security and privacy: building robust AI systems to detect and defend them against adversarial attacks; (4) sustainability: it is essential to reduce energy consumption with sustainability regulations because AI-based services have increasingly become a major factor in rising energy consumption.

4. Conclusion

In this paper, we present a scoping review to clarify the concept of trustworthiness in multi-agent UAV systems, focusing on reliability, security, sustainability, explainability, and fairness. Moreover, promising future works could be considered such as exploring distributed learning, blockchain, and advanced cryptographic primitives to enhance security and privacy challenges Zuo et al. (2023); investigating the power of quantum computing enhancing energy efficiency Wang and Rahman (2022); adopting semantic methods to emphasize explanations by understanding the common-sense reasoning Yang et al. (2023); examining LLMs or agentic AI to deploy trust systems Tran et al. (2025).

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