Formalizing the Concept of Hive Mind and Organizing Technologies for a UAV Swarm Hive Mind Framework

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***Abstract*—The concept of a hive mind has been widely referenced to describe systems where multiple autonomous agents collectively operate as a single, cohesive entity. However, the term remains informally defined within academic and technical contexts, particularly in relation to autonomous systems. This paper aims to formalize the hive mind concept and apply it to UAV swarm systems, where unmanned autonomous vehicles collaborate to execute complex tasks. We propose a Generalized modular framework that organizes the essential technologies and control mechanisms for a UAV swarm hive mind, balancing centralized coordination with decentralized autonomy. Additionally, we conduct a comprehensive survey of relevant technologies that could contribute to this framework, covering communication systems, knowledge sharing, task allocation, decision-making, and learning algorithms. By organizing these technologies into a unified framework, we outline a path for implementing UAV swarm hive minds and identify key challenges and future directions for integrating these technologies into real-world applications.**

***Index Terms*—Hive Mind, Swarm Robotics, Swarm Intelligence, UAV, Autonomous Systems, Large Language Models, Hybrid AI**

I. Introduction

UAV swarms have become increasingly important across various domains, including military operations, disaster response, and smart cities. In military contexts, UAV swarms are utilized for coordinated surveillance and reconnaissance missions in hostile environments, which not only improves data collection efficiency but also reduces risks for human personnel [1]. In disaster scenarios, UAV swarms can rapidly conduct search and rescue operations by dividing large areas into smaller, manageable sections. This approach enables multiple UAVs to work in parallel, covering extensive regions efficiently and providing real-time data to first responders, significantly enhancing communication and response times [2], [3]. Similarly, in smart cities, UAV swarms play an essential role in traffic management, environmental monitoring, and infrastructure inspection, offering real-time data that supports urban planning and improves public safety [4]. The autonomous operation, efficient route planning, and real-time collaboration of UAV swarms make them indispensable in such complex environments.

The rise of Large Language Models (LLMs) and Transformer models has brought a paradigm shift in artificial intelligence by enabling systems to process vast amounts of data with high precision. These models excel in generalization, contextual understanding, and making complex decisions based on nuanced inputs, outperforming traditional rule-based systems and reinforcement learning approaches [5]. The integration of LLMs into autonomous systems introduces new opportunities for decision-making and strategic coordination, particularly in environments that demand real-time adaptation and intricate task planning. For example, LLMs can map natural language inputs to domain-specific commands, allowing autonomous vehicles to generate real-time simulations and make decisions based on high-level directives [6]. Additionally, Transformer models with structural guidance capabilities enable autonomous systems to mimic human-like linguistic generalization, fostering more natural and intuitive interactions between machines and humans [7]. As a result, LLMs and Transformer models have emerged as promising tools for enhancing the coordination and adaptability of autonomous systems, from self-driving vehicles to military operations [8].

However, the concept of a hive mind remains largely informal in the realm of autonomous systems, leading to inconsistencies and ambiguity in research. To address this, the paper aims to establish a formal, structured definition of hive mind, providing a consistent framework applicable across various fields involving multi-agent systems, particularly UAV swarms. Based on this formal definition, we propose a high-level framework for a UAV swarm hive mind that emphasizes centralized knowledge sharing combined with hybrid control mechanisms. This hybrid approach integrates centralized decision-making for strategic guidance with decentralized autonomy for real-time execution, enabling UAVs to adapt to dynamic environments. Furthermore, the paper surveys the key core modules that constitute this framework, including centralized cognitive core, collective collective knowledge network,task management and allocations, local autonomous sensing and execution modules.

II. Background and the Need for Formalization

To understand the concept of hive mind in the context of UAV swarms, it is essential to explore the underlying paradigms that govern how autonomous agents interact, make decisions, and share knowledge. These paradigms provide the foundation for developing a coherent framework where distributed systems function both independently and collectively to achieve complex objectives.

A. Distributed Decision-Making Paradigms

Swarm Intelligence refers to a decentralized decision-making paradigm where individual agents, such as UAVs, follow simple rules and interact locally, resulting in complex collective behavior. In this paradigm, agents do not rely on central control but instead use local interactions to coordinate their activities. This principle is particularly useful in UAV systems, where multiple drones need to collaborate in real-time to complete tasks such as search and rescue, surveillance, and environmental monitoring. Swarm robotics, an application of swarm intelligence, uses these principles to coordinate large numbers of autonomous UAVs, enabling behaviors such as formation flying, cooperative navigation, and dynamic task allocation [9]. In such systems, nature-inspired algorithms like stigmergy and flocking are often employed to drive the behavior of individual UAVs, making the system robust, scalable, and flexible in handling dynamic environments [10], [11].

Multi-Agent Systems (MAS) provide a framework in which autonomous agents collaborate or compete to achieve shared objectives. In the context of UAV systems, MAS allows individual drones to work together to accomplish complex tasks such as search-and-rescue, surveillance, and environmental monitoring. Each UAV operates semi-independently, using local knowledge while coordinating with other agents to ensure task completion, thereby enhancing overall system efficiency [12], [13]. MAS enables UAV swarms to dynamically allocate tasks, avoid conflicts, and adapt to changing environments, making them robust and scalable for a wide range of applications [14].

Collective Intelligence refers to the ability of a group of agents to work together to solve complex problems without centralized control. Unlike swarm intelligence, where agents follow simple local rules and interact only within their immediate environment, collective intelligence emphasizes a more collaborative approach, with agents often pooling their knowledge to achieve a common goal. In UAV systems, this can manifest through shared situational awareness and collaborative decision-making, allowing the swarm to adapt to dynamic environments [15]. While similar to swarm intelligence, collective intelligence typically involves more complex interactions and greater reliance on communication between agents [16].

B. Distributed Cognition

Distributed cognition refers to the theory that cognitive processes are not confined to a single agent but are distributed across agents, artifacts, and their environment. In UAV systems, this concept serves as the foundation for shared decision-making, where the swarm collectively processes information from various sources such as onboard sensors, networked datalinks, and shared knowledge bases. This allows the system to adapt in real time to dynamic environments without relying on a central controller [17]. The integration of distributed cognition into multi-agent systems enables UAVs to function autonomously while collaborating effectively in missions like surveillance and target acquisition, by sharing information and making decisions cooperatively [18]. This approach minimizes cognitive load on individual agents, creating a more efficient, robust, and scalable coordination mechanism for complex missions [19].

C. The Concept of Hive Mind and Its Distinguishing Features

The concept of the hive mind builds upon the paradigms of swarm intelligence, collective intelligence, and multi-agent systems (MAS) by integrating both centralized and decentralized control. In contrast to purely decentralized systems, where decisions are made entirely by individual agents, the hive mind utilizes a hybrid control structure. This enables high-level strategic decisions to be made centrally, while agents retain local autonomy to handle immediate, environment-specific challenges. This dual control structure enhances both the flexibility and robustness of UAV swarms, enabling agents to adjust their actions based on global directives and localized data. For example, in military operations, centralized oversight might define the overall mission objectives, while individual UAVs independently navigate and adapt to obstacles or threats.

Another core feature of the hive mind is global knowledge sharing. Agents within the swarm continually update and access a shared knowledge repository, which enables the system to maintain global awareness. This collective pool of knowledge allows each agent to make informed decisions based on both local data and the broader state of the system. The integration of technologies such as cloud-based communication platforms and distributed databases facilitates this seamless exchange of information. In practical terms, this could be applied in disaster response missions, where each UAV contributes real-time data to a centralized knowledge pool, enabling the swarm to act in a coordinated, informed manner while covering large areas rapidly.

Finally, real-time collective decision-making is a critical aspect of the hive mind. While individual UAVs possess the autonomy to act based on their immediate environment, their decisions are continuously informed by the global state of the system. This allows the swarm to function as a single cohesive unit, capable of dynamically coordinating its actions in response to rapidly changing environments. For instance, in a search-and-rescue mission, individual UAVs may detect different sections of the terrain, but they collectively adjust their flight paths and priorities based on real-time updates from the entire swarm. This ensures that the system as a whole responds in an adaptive and efficient way to emerging challenges.

D. The Need for Formalization

The term ”hive mind” is frequently used in both academic literature and popular discourse, but its definition remains ambiguous, particularly when applied to autonomous systems like UAV swarms. In some contexts, the hive mind is understood as a decentralized system where agents autonomously collaborate while sharing information in real-time. For example, in the Grex model, distributed ledger technology (DLT) enables agents to autonomously update shared knowledge bases without central oversight, allowing for effective decision-making at the agent level [20]. Such decentralized systems emphasize the autonomy of individual agents, relying on continuous knowledge sharing to maintain collective intelligence.

However, other interpretations of the hive mind involve centralized or hybrid systems, where some level of centralized control is maintained to oversee high-level decision-making. The Hive model, for instance, features distributed agents but incorporates centralized nodes that influence global coordination, particularly in task allocation [21]. Additionally, in certain hybrid systems, centralized control is employed to manage critical decision points, while decentralized control is reserved for localized operations [22]. This hybrid control strategy can be observed in UAV swarms that rely on both local autonomy and high-level centralized directives to optimize mission performance [23].

This lack of consensus regarding the balance between decentralized and centralized control has led to significant confusion in defining what constitutes a true hive mind in multi-agent systems. Some researchers define the hive mind as a system in which agents fully retain their autonomy while contributing to collective decisions through real-time knowledge sharing, as seen in swarm intelligence models [10]. Conversely, others apply the term to systems that rely on a hierarchical structure, where decision-making is primarily controlled by central nodes informed by the data provided by autonomous agents [24]. This inconsistency in defining knowledge sharing, decision-making autonomy, and control structure creates challenges in establishing standardized frameworks for UAV swarms and other autonomous systems.

The practical implications of this ambiguity are profound. In decentralized hive mind systems, latency and data synchronization issues can arise when agents must share information in real-time over large networks. These challenges can be particularly problematic in disaster response scenarios, where UAVs need to coordinate quickly to cover large areas, and delays in knowledge sharing can lead to mission inefficiency or failure. On the other hand, more centralized systems may struggle with scalability, as decision-making bottlenecks can slow down the entire swarm's response time in critical situations, such as military operations or search-and-rescue missions [25]. The absence of a formalized and universally accepted definition of the hive mind makes it difficult for engineers and researchers to design optimized UAV swarm systems, often leading to conflicting strategies that reduce overall system effectiveness.

Ultimately, the varied interpretations of hive mind reflect the broader tension between centralized and decentralized control in autonomous systems. The need for a unified definition is crucial, as this would help clarify how characteristics like global knowledge sharing, real-time decision-making, and agent autonomy are integrated across different systems. As hybrid control models become more prevalent, a clear understanding of the hive mind will allow for better coordination in complex autonomous missions, enhancing the efficiency, scalability, and robustness of UAV swarms.

The increasing complexity of UAV systems is largely driven by the growing demand for real-time decision-making capabilities and the integration of emerging technologies such as Large Language Models (LLMs). In the past, UAV systems primarily relied on traditional algorithms for task execution and coordination, but recent advancements in LLMs have opened new possibilities for more advanced and context-aware decision-making. For instance, LLMs enable UAVs to understand and process natural language inputs, making them capable of adapting to dynamic environments by interpreting complex instructions and making decisions in real time. In the broader field of robotics, LLMs have already demonstrated their potential in enhancing robot intelligence, enabling more seamless interactions between robots and their environments [26]. This capability directly impacts the evolution of UAV swarms, as they increasingly require sophisticated coordination mechanisms that can handle a wide array of missions with minimal human intervention.

In swarm robotics, the potential of LLM-based agents has begun to emerge. LLMs are proving to be effective in enabling multi-robot collaboration, where agents can communicate, reason about task strategies, and adjust plans based on environmental feedback. Studies such as RoCo have shown how LLMs can enhance collaboration between robots by using natural language to coordinate and optimize collective behavior [27]. By leveraging the natural language processing abilities of LLMs, UAV swarms can exchange complex data more efficiently, reducing communication bottlenecks and improving overall system performance. This represents a significant step forward in swarm intelligence, as it allows agents to maintain real-time awareness of their surroundings and adapt their actions accordingly, all while interacting naturally with humans or other systems.

The integration of LLMs into UAV swarm systems not only increases operational complexity but also highlights the need to formalize concepts like the hive mind. As UAV swarms incorporate LLM-based technologies to facilitate real-time decision-making and knowledge sharing, the boundaries between centralized and decentralized control become increasingly blurred. Hybrid models that combine autonomous local decision-making with centralized high-level directives are becoming more prevalent, as seen in systems like Swarm-GPT, which integrates LLMs for safe swarm motion planning [28]. This evolving complexity further underscores the necessity of a clear and formal definition of the hive mind, as it becomes crucial to standardize how these systems handle real-time decision-making, knowledge sharing, and coordination in dynamic and large-scale environments.

III. Formal Definition of Hive Mind

A. Proposed Definition

A hive mind is a system of distributed autonomous agents (such as UAVs) that function as a single, coherent entity by leveraging centralized collective cognition and distributed execution. Unlike purely decentralized systems, where each agent acts independently based on local data, a hive mind integrates global awareness and shared consciousness across all agents, allowing them to act as part of a unified cognitive framework. Agents contribute to and draw from a centralized collective intelligence that provides mission directives and processes data from the swarm, ensuring that decisions made by individual agents align with global mission objectives. This architecture allows agents to exhibit local autonomy while ensuring their actions are guided by real-time knowledge sharing and collective decision-making, enabling the system to respond efficiently to dynamic environments and complex tasks with organism-like coordination.

B. Key Characteristics of a Hive Mind

Hybrid Control Mechanism: The hive mind operates under a hybrid control model, where centralized collective cognition drives global strategic decisions, and agents retain local autonomy for execution. Unlike traditional decentralized systems, agents in a hive mind are informed by global directives and act in concert with the central consciousness, rather than simply reacting to local stimuli. This combination of global coordination and localized adaptation ensures that the swarm behaves as a single, intelligent entity, responding in real-time to evolving conditions. In UAV swarm applications, this hybrid control has been shown to enhance both robustness and scalability by distributing the cognitive load without compromising global coherence [29]. By balancing centralized decision-making with localized execution, the system ensures mission efficiency without overwhelming any single decision node.

Global Knowledge Sharing: A key feature of the hive mind is its ability to maintain a centralized repository of shared knowledge that all agents continuously update and access. This enables the swarm to operate with global awareness, where each agent's decisions are informed by both local data and the collective state of the entire system. The centralized collective intelligence processes this incoming data and refines the global strategy, allowing the swarm to adjust its behavior in real time. Multi-agent reinforcement learning has further improved the ability of agents to contribute meaningfully to the shared knowledge pool, enabling more efficient coordination in tasks such as target search and environmental monitoring [30]. Unlike purely decentralized systems, where knowledge sharing is limited, a hive mind ensures that all agents act with a holistic understanding of the mission.

Real-Time Collective Decision-Making: One of the most powerful aspects of a hive mind is its capacity for real-time collective decision-making, where each agent's decisions are not made in isolation but are informed by the global consciousness of the swarm. This enables the swarm to dynamically adapt to changes in the environment, re-prioritizing tasks, and optimizing its strategy in real time. In scenarios such as military confrontations or disaster response, this capacity for coordinated action ensures that the swarm acts as a unified entity, capable of adjusting to rapidly evolving conditions without losing coherence [31]. The real-time synchronization of actions ensures that agents do not operate independently but instead coordinate seamlessly, leading to higher levels of mission success and operational efficiency.

Scalability and Adaptability: The hive mind is inherently scalable, capable of integrating large numbers of agents while maintaining a sense of cohesion and unified action. As new agents are introduced into the system, they seamlessly become part of the centralized collective intelligence, contributing to the shared knowledge base and aligning their behavior with the global strategy. The system is highly adaptable, able to modify its global mission objectives and local task assignments in response to changing conditions without requiring manual reconfiguration. This makes the hive mind particularly suited to large-scale operations, such as search-and-rescue missions, where the swarm can adapt dynamically to new objectives or unexpected challenges [32].

Agent Autonomy with Global Awareness: Agents within the hive mind retain a high degree of local autonomy while remaining fully aware of the global mission objectives and the state of the swarm. This enables agents to make independent decisions when necessary, such as avoiding obstacles or optimizing their individual tasks, while ensuring that their actions align with the swarm's overall global strategy. This global awareness allows agents to act not just as individual units but as parts of a larger, unified system, driven by collective intelligence. In complex environments such as cooperative air combat, where agents must balance autonomy with real-time updates from the swarm, this dual capability ensures that each agent functions within the broader context of the swarm's goals [33]. In addition to this autonomy, agents can interact with one another to exhibit emergent behaviors commonly observed in swarm intelligence, allowing the collective behavior of the swarm to exceed the capabilities of individual agents.

IV. A Modular and Future-Proof UAV Swarm Hive Mind Framework

This Framework is designed as a highly generalized framework without focusing on specific implementation details, allowing it to remain flexible and adaptable across diverse use cases. By defining core principles and modules, it provides a flexible foundation that can be customized for specific applications while ensuring the swarm behaves as a unified, intelligent system.

A. Design Principles for the Framework

The architecture follows several key principles that ensure flexibility, scalability, and adaptability across different mission types:

Centralized Cognition with Flexible Deployment: The system includes a centralized cognitive core responsible for global

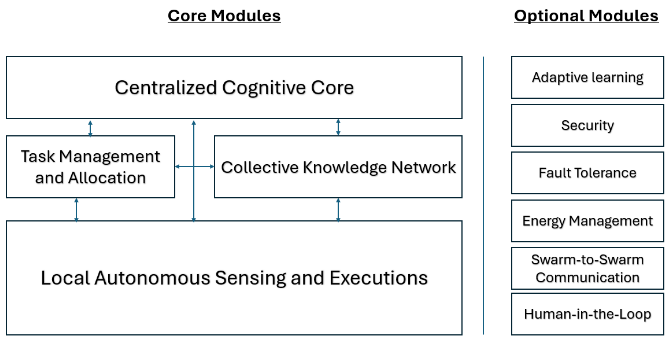

Fig. 1. Modularized UAV Swarm Hive Mind Framework

decision-making. Depending on mission requirements, this core can be centralized or distributed across UAVs.

Shared Knowledge and Global Awareness: UAVs continuously share real-time information, enabling each agent to make local decisions that are informed by global mission objectives.

Unified and Coordinated Action: UAVs operate autonomously at the local level but follow global directives, ensuring that the swarm acts as a cohesive unit.

Dynamic Task Allocation: Tasks are dynamically assigned and reassigned in real time based on the UAVs' capabilities, mission status, and environmental changes.

Resilience and Adaptation: The architecture is designed to be resilient, capable of self-healing and adapting dynamically to changes in the environment or mission objectives.

Scalability and Modularity: The framework is scalable, supporting both small and large swarms, and is modular, allowing easy integration of new technologies and additional capabilities.

B. The Four core modules

Centralized Cognitive Core (Virtual Central Intelligence) The Centralized Cognitive Core serves as the brain of the hive mind, responsible for centralized decision-making and processing the global state of the system. It collects information from all UAVs, formulates a global mission strategy, and issues directives that synchronize the actions of individual agents. Its primary purpose is to ensure the system behaves as a single entity by continuously refining and adapting the overall plan based on mission progress and environmental changes.

The cognitive core maintains a high-level overview of the mission objectives and the swarm's overall status. It processes data from the UAVs and sensors, creating and updating a global plan that directs the swarm's collective actions. While individual UAVs make local decisions, the central cognitive core has the final say on global directives, refining the global strategy in real-time as the mission evolves.

The core can either be distributed among UAVs or hosted in a cloud-based system, depending on the mission's infrastructure. In a distributed model, cognitive processes are shared among agents, whereas in a cloud-based model, a central system communicates with each UAV.

For example, in a search-and-rescue mission, the cognitive core processes data from all UAVs, updates the search grid, and ensures that no area is missed. It dynamically adjusts UAVs to focus on high-priority tasks, such as responding to detected survivors, based on real-time feedback from the field.

Collective Knowledge Network (Shared Consciousness) The Collective Knowledge Network provides the shared consciousness essential for a hive mind. It ensures that all agents in the swarm are continuously aware of the global state of the mission. This module synchronizes data between UAVs, ensuring that every agent has real-time access to information regarding task status, environmental conditions, and the positions of other agents.

Each UAV shares its sensor data, status, and task progress with the entire swarm in real time, allowing agents to make decisions based on both local and global knowledge. The knowledge network can be implemented using a distributed system, such as a blockchain or distributed ledger, where data is stored and synchronized across all agents. This prevents a single point of failure and ensures that all agents maintain up-to-date knowledge, even in the case of communication issues.

Each agent is aware not only of its local environment but also of where other agents are, what they are doing, and the current global mission status. This global awareness allows UAVs to make informed decisions and avoid conflicts or duplication of efforts.

For instance, in a forest fire monitoring mission, each UAV collects data about fire intensity and movement and updates the shared knowledge base. This enables all UAVs to adjust their paths and focus their efforts on the most critical areas without redundant coverage.

Task Management and Dynamic Allocation(Adaptive Tasking) The Task Management and Dynamic Allocation module plays a critical role in ensuring that the UAV swarm operates efficiently and adapts to changing mission needs. This module dynamically assigns and reallocates tasks to UAVs based on their current capabilities, real-time location, and evolving environmental conditions. By continuously monitoring the status of each UAV and the progress of the mission, this module optimizes resource allocation and ensures that UAVs can assume different roles as the mission evolves, thus maximizing mission efficiency.

This module operates in close coordination with the Centralized Cognitive Core and the Collective Knowledge Network. It gathers data on each UAV's performance and updates tasks based on real-time feedback from the field. The module evaluates factors such as battery life, sensor status, proximity to mission objectives, and UAV capabilities to allocate tasks in a way that maintains overall mission efficiency and prevents UAVs from being overburdened or underutilized.—

In addition to real-time task reassignment, the Task Management module works with the Autonomous Local Execution and Adaptation module to allow UAVs to take immediate local actions based on environmental changes. However, higher-level task reassignments and mission-wide decisions remain under the oversight of the Task Management module, ensuring a balance between local autonomy and global coordination.

For example, during a search-and-rescue mission, if one UAV encounters a challenging obstacle or requires immediate recharging, nearby UAVs can temporarily take over its tasks. The Task Management module will reassign the affected UAV's remaining tasks to the most suitable agents, thus maintaining mission progress without interruptions.

Autonomous Local sensing and Execution(Local Autonomy) The Autonomous Local Sending and Execution module provides each UAV with the autonomy to execute tasks independently while being informed by global directives and collective knowledge. This module ensures that agents can adapt to local environmental changes and carry out their assigned tasks while remaining synchronized with the overall mission.

Each UAV is equipped with onboard intelligence that allows it to make real-time decisions about navigation, obstacle avoidance, and task execution based on its local environment. Although UAVs act independently, their local decisions are influenced by global mission directives and shared knowledge, allowing them to adjust their actions according to the broader swarm's needs. Furthermore, agents communicate with other UAVs in the swarm, allowing for swarm intelligence type emergent behaviors, where collective behaviors emerge from simple interactions between agents, enhancing the overall efficiency and adaptability of the swarm.

For example, in a military surveillance mission, a UAV may autonomously decide to avoid an unexpected obstacle, such as enemy activity, while still updating the swarm on its location and task status. Other UAVs adjust their actions accordingly, ensuring that the overall surveillance plan remains intact without requiring explicit instructions from the cognitive core.

C. Optional and Future-Proofing Modules

To enhance the framework's flexibility and prepare for future technologies, several optional modules can be integrated as needed. These modules provide additional functionality and allow the system to be easily upgraded for more advanced missions.

The Adaptive Learning and Continuous Improvement module allows UAVs to learn from past missions and refine their behavior over time. Using machine learning techniques such as reinforcement learning, this module enables the UAVs to adapt to new environments and optimize their task execution for future operations.

The Security and Trust Management module ensures that the swarm operates in a secure environment, protecting data and communication channels from potential threats. It manages encryption, secure communication protocols, and trust mechanisms between UAVs, preventing malicious agents or tampered data from affecting the mission.

Fault Tolerance and Self-Healing is another critical module that enhances the framework's robustness. It allows the swarm to detect agent failures or malfunctions and reconfigure itself automatically to continue the mission. If a UAV becomes incapacitated, the remaining UAVs dynamically adjust their tasks to cover the failed agent's responsibilities.

The Energy Management and Optimization module monitors the energy consumption of each UAV and ensures that tasks are assigned based on available power. This module allows the system to optimize battery usage, extend mission duration, and coordinate UAV recharging. Energy management is crucial in ensuring the swarm's operational efficiency, especially during long-duration missions.

The Swarm-to-Swarm Communication and Collaboration module enables the UAV swarm to interact and coordinate with other autonomous swarms or systems. This module facilitates multi-swarm collaboration, allowing separate UAV swarms to exchange data, share tasks, and synchronize mission objectives. By integrating this module, different swarms can operate cohesively in large-scale missions that require cross-swarm coordination.

The Human-in-the-Loop Control module enables human operators to provide high-level guidance or intervene when necessary. While the system is designed to function autonomously, certain mission-critical scenarios may require human oversight. This module allows for seamless transitions between full autonomy and human-guided interventions.

D. Flow of Control and Data

Centralized Cognitive Core: The Cognitive Core continuously processes data from all UAVs, updating the global mission strategy and issuing directives that guide the swarm's behavior. This ensures that the swarm acts with unified intent, adapting its overall strategy based on real-time inputs from the field.

Collective Knowledge Network: The Knowledge Network ensures that each UAV has access to shared knowledge, including mission status, UAV positions, and environmental factors. This enables UAVs to act locally with autonomy while remaining synchronized with the swarm's global mission objectives. Real-time data sharing ensures that all UAVs are informed of the latest developments and can adapt accordingly.

Task Management and Dynamic Allocation: Task management is coordinated by the Cognitive Core, which dynamically assigns and reallocates tasks to UAVs based on real-time mission requirements and agent status. UAVs receive high-level task directives but retain the flexibility to adapt locally based on environmental conditions. The Cognitive Core constantly monitors UAV performance, reassigning tasks to ensure optimal resource utilization and mission efficiency.

Autonomous Local Execution: UAVs execute tasks with local autonomy, making real-time decisions and adjustments based on environmental feedback and sensor data. While operating independently, each UAV continuously contributes local data to the collective knowledge base, ensuring alignment with the global mission strategy through regular updates and synchronization.

Citation	Research Focus	Methodology	Significance/Innovation
[34]	Decision-making in UAV combat swarms	PSO and behavior trees	Achieved 93% efficiency in threat elimination
[35]	Mission decision-making for UAV swarms	Hybrid DBN	Improved decision accuracy by 25.03%
[36]	Cooperative search algorithm in swarms	PSO	Prevents UAV clustering, improves search efficiency
[37]	Automated maneuvering for surveillance	Game tree decision algorithm	Optimized collision avoidance and formation maintenance
[38]	Collaborative decision-making of UAVs	Fuzzy cognitive map (FCM)	Enhances autonomy and reduces control burden
[39]	Cooperative coverage control in UAVs	EPPO (Deep RL)	Efficient and safe area search coverage
[40]	Flocking control in UAV swarms	Deep RL (POMDP)	Centralized training, decentralized execution
[41]	Collaborative tasks for UAV swarms	DDQN	Achieved 90% success rate in mission execution
[42]	Flocking and navigation of UAVs	Deep RL	Large-scale navigation in complex environments
[43]	Coordinated UAV control in mobile access	MADRL (CTDE)	Improved cooperation in multiple-agent systems
[10]	Autonomous intelligence in target search	AI-based bivariate potential fields	Enhanced target search effectiveness in swarms
[9]	UAV swarm systems with AI	AI for object recognition, route planning	Integration of AI for complex mission tasks
[44]	AI-driven decision-making in UAV swarms	AI with RL and PSO	Promoted decision-making using AI methods for coordination
[45]	AI-based combat maneuver decisions for UAVs	Multi-agent Transformer	Structured situation processing for combat maneuver decisions
[46]	Centralized decision-making using VR for UAV swarms	Multimodal AI interface	Use of VR and AI for centralized swarm control
[47]	Command and control for UAV swarms	Agent-based modeling	Highlights potential use of LLM for swarm decision-making
[48]	Decision paradigms for UAV swarms	LLM-like structure in decision-making	Presents a new decision-making paradigm for UAV swarms
[49]	Command and control of UAV swarms	Agent-based modeling	Demonstrates need for advanced decision-making models like Transformers
[50]	UAV swarm inspection with reconfigurable drones	Transformer links	Enhances formation integrity with virtual impedance links for complex environments
[51]	Real-time surveillance using quadcopter UAVs	Autonomous surveillance systems	Improves real-time coverage for smart cities
[52]	Swarm intelligence for UAV air combat	Ant colony algorithm	Improved success rate in combat through coordinated attacks
[53]	Autonomous decision-making in manned/unmanned air combat	AI-guided target tracking and guidance	Improved real-time decision-making in combat
[54]	Immune network-based swarm intelligence for UAV coordination	AI cooperative operation strategy	Demonstrates immune network-based strategy for swarm control
[55]	Robust self-organizing UAV swarm with loss compensation strategies	AI-driven self-organization	Ensures mission continuity even with UAV losses during operation
[56]	Adversarial impacts on decentralized UAV swarms	AI-based swarm resilience	Highlights vulnerabilities and hazards in swarm operations under external influences
[57]	UAV swarm control system simulation	AI-based control simulation	Simulates centralized control strategies for UAV swarm behavior
[58]	SAC-OD rules for UAV swarm conflicts	Improved SAC-OD rules	Enhances UAV swarm confrontation strategies using dynamic interaction
[59]	UAV swarm path planning	Centralized control algorithms	Improves swarm path planning efficiency for large UAV groups
[23]	Fixed-wing UAV swarm system control	Decentralized decision-making	Enables autonomy and collision avoidance in large UAV swarms
[60]	Decentralized formation shape control for UAV swarms	Decentralized Markov Decision Process (Dec-MDP)	Proposes a decentralized control approach for UAV swarms using dynamic programming

TABLE I
SURVEY FOR THE CENTRAL COGNITIVE CORE

V. SURVEY OF CORE MODULES OF THE FRAMEWORK

A. Centralized Cognitive Core

The centralized cognitive core in UAV swarms plays a pivotal role in managing global decision-making, task allocation, and mission strategies, ensuring that individual UAVs operate cohesively under central directives. As detailed in Table 1, which surveys works related to this core, several papers emphasize advancements in algorithms, artificial intelligence (AI), and centralized control methods. For example, [10], [39], and [45] demonstrate how AI models such as multi-agent Transformers and reinforcement learning algorithms optimize decision-making and task coordination in complex environments. These works underline the importance of integrating real-time updates and collaborative frameworks to ensure effective UAV swarm performance.

Key insights from these papers highlight the growing use of hybrid control systems that combine centralized directives with localized autonomy. Papers such as [35], which employs a Hybrid Variable Structure DBN, show an improvement in decision-making accuracy by 25.03%. Similarly, studies like [58] and [44] indicate a trend towards leveraging AI for task allocation and dynamic conflict resolution within UAV swarms. The common focus across these works is to enhance mission efficiency and adaptability, particularly in challenging environments such as air combat and search missions.

Citation	Research Focus	Methodology	Significance/Innovation
[61]	Blockchain-based data sharing in UAV swarms	Blockchain technology	Secure, decentralized communication between UAVs
[62]	Gossip protocols for managing UAV data sharing	Adaptive gossip protocols	Manages redundancy and improves security in dense networks
[63]	Decentralized data management in UAV swarms	Blockchain-based model	Ensures data integrity and secure communication
[64]	P2P and pub/sub hybrid communication system	Peer-to-peer (P2P) and pub/sub	Efficient decentralized information exchange in swarms
[65]	Distributed logging in cloud environments	Distributed Hash Table (DHT)	Provides a scalable architecture for logging services in distributed networks
[66]	Hybrid cloud implementation for distributed databases	Performance evaluation of databases	Analyzes performance of distributed databases such as MongoDB and MySQL in cloud-burst scenarios
[67]	Query-adaptive Distributed Hash Table	Partial DHT implementation	Outperforms traditional indexing by indexing only frequently queried keys
[68]	In-network distributed hash tables	Data plane programmability	Improves performance of distributed hash tables using in-network data plane programming
[69]	Cooperative UAV flight planning	Distributed trajectory planning	Utilizes Monte Carlo Tree Search and PSO for effective cooperative UAV trajectory planning
[70]	Cloud-in-cloud for virtualized datacenters	Hosted hypervisor	Supports multiple virtualized datacenters, ideal for cloud-to-cloud scenarios
[71]	Federated cloud environments	Technology-neutral interfaces	Provides architecture for virtual machine placement and monitoring across federated clouds
[72]	Serverless platform for joint cloud computing	HCloud serverless model	Efficient workload migration across multiple clouds, enhancing service quality
[73]	SDN Virtual Networks for cluster clouds	Cluster cloud architecture	Centralized-to-distributed cloud transitions for reducing network data usage
[74]	Hybrid cloud service integration	Hybrid cloud framework	Enables management and control of integrated on- and off-premise cloud environments
[75]	Aloha MAC protocol for satellite communication	Decollision algorithm, spot beam technology	Achieved up to 90% higher throughput compared to traditional Aloha protocols
[76]	Adaptive MAC framework for UAV ad hoc networks	CSMA and TDMA switching	Enables UAVs to switch communication modes based on positions for reconnaissance missions
[77]	Energy-efficient MAC protocol for WPSNs	Improved Sensor MAC (IS-MAC)	Reduces energy consumption by adjusting contention window based on network load
[78]	Hybrid MAC protocol for underwater sensor networks	Reservation and contention-based MAC	Optimizes traffic load and supports access of autonomous vehicles like AUVs
[79]	Joint communication and action learning in UAV swarms	Deep reinforcement learning	Enhances multi-target tracking and communication efficiency in UAV swarms
[80]	Aggregation transfer learning for UAV swarms	Multi-agent reinforcement learning (MADDPG)	Adapts small-scale training to larger environments using graph neural networks
[81]	Real-time communication provision in UAVs	Mobile relay communication	Facilitates real-time knowledge sharing through mobile relay UAVs in remote areas
[82]	Secure broadcast protocol for UAV swarms	Swarm Broadcast Protocol (SBP)	Ensures secure real-time communication with low overhead in leader-follower formations
[83]	Real-time coordination of UAV swarms	Bandwidth-efficient multi-robot coordination algorithm	Supports real-time knowledge sharing over mobile networks with low latency
[84]	Hierarchical mesh architecture for QoS	Hierarchical resource management	Reduces co-channel interference and optimizes resource management in mesh networks
[85]	Mesh networks as ad hoc network alternatives	Commodity multihop ad hoc networks	Surveys core technologies for cost-effective, high-performance mesh networking
[86]	Autonomous Mobile Mesh Networks	Mobile mesh nodes and topology adaptation	Addresses network partitioning and improves connectivity in ad hoc mobile networks
[87]	Cooperative communication in MANETs	Clustered and decentralized cooperative communication	Improves network connectivity with centralized relays and decentralized links

TABLE II

SURVEY FOR THE COLLECTIVE KNOWLEDGE NETWORK

B. Collective Knowledge Network

The Collective Knowledge Network in UAV swarms facilitates real-time data sharing, synchronization, and decentralized or centralized knowledge management. As outlined in Table 2, which surveys works on this topic, research focuses on distributed databases, decentralized data-sharing frameworks, communication protocols, and real-time knowledge updates. For instance, papers like [61] explore blockchain-based data sharing and decentralized multi-agent resource allocation to ensure secure and efficient knowledge distribution across UAVs. Meanwhile, [79] leverages deep reinforcement learning for optimizing communication and task execution within UAV swarms, highlighting advanced methodologies for dynamic collective updates.

Key insights reveal a shift toward hybrid and decentralized systems, integrating technologies like blockchain, multi-agent reinforcement learning, and mesh networks. Papers such as [84] showcase the efficiency of hierarchical architectures in improving resource management and co-channel interference, while [83] emphasizes the importance of real-time coordination and bandwidth-efficient communication.

Citation	Research Focus	Methodology	Significance/Innovation
[88]	Task assignment and trajectory optimization	Genetic algorithm (MPGA)	Improved efficiency in task assignment and UAV trajectories
[89]	Dynamic target search for UAVs	MAPPO algorithm	26.97% higher success rate in dynamic target search
[90]	Multi-task assignment in UAV formations	Distributed auction algorithm	Efficient task allocation in air combat scenarios
[91]	Decentralized task assignment for UAVs	Genetic algorithm	Facilitates decentralized task allocation with limited communication
[92]	Local real-time task allocation for UAVs	Improved CNP approach	Optimizes resource consumption and task completion in communication-constrained environments
[93]	Real-time scheduling for UAV groups	Randomized local voting	Enhances dynamic rescheduling with local voting for task redistribution
[94]	Task pre-allocation and dynamic reallocation	Particle swarm optimization, contract network protocol	Adapts to changing mission needs with real-time task reassignment
[95]	Dynamic task assignment in UAV swarms	Auction and consensus mechanism	Provides conflict-free task assignments using real-time reallocation
[96]	Dynamic task reallocation for multi-UAVs	Redistribution and adjustment strategies	Enhances task performance in changing environments through dynamic reallocation
[97]	Trajectory planning for energy-constrained UAVs	Q-learning	Reduces energy consumption while improving task completion rates
[98]	Energy-saving multi-UAV deployment	DRCHK and DRCKM algorithms	Optimizes energy use for task-oriented UAV deployments
[99]	Energy-aware task allocation in MEC systems	Ant Colony System (ACS)	Minimizes energy consumption in multi-UAV edge computing tasks
[100]	Energy-efficient task scheduling in edge computing	Differential evolution and greedy algorithm	Joint optimization of UAV deployment and task scheduling
[101]	Energy-efficient task offloading in UAV networks	Green-UAV-CoCaCo algorithm	Enhances energy efficiency through optimization of communications, caching, and computation
[102]	Collaborative task assignment for multi-UAV	Cluster structure	Balances task loads and improves optimization capabilities in decentralized settings
[103]	Decentralized task coordination in swarm robotics	CDTA-CL and CDTA-DL algorithms	Optimizes task allocation and reduces power consumption in decentralized systems
[104]	Task allocation in UAV clusters	Quantized particle swarm optimization	Improves convergence speed and adaptability over traditional algorithms
[105]	Dynamic task allocation in UAV swarms	Binary wolf pack algorithm (BWPA)	Enhances real-time performance and adaptability to changing environments
[106]	Real-time dynamic planning in UAV teams	Consensus-Based Bundle Algorithm (CBBA)	Improves network connectivity and mission performance under uncertainty
[107]	Mission planning in dynamic environments	Hybrid artificial potential field and ant colony optimization	Optimizes task execution and obstacle avoidance under uncertainty
[108]	Task assignment for unmanned vehicles	Mixed-initiative scheduling	Improves operator interaction with task scheduling systems under uncertain conditions
[109]	Decentralized control for collaborative missions	Decentralized task allocation	Adapts to uncertainties and communication losses while minimizing mission costs
[110]	UAV autonomy and mission control levels	Information flow and secured communication	Emphasizes how UAVs minimize human interaction with autonomous mission control
[111]	Autonomous path control for UAVs	Embedded mission control	Enhances autonomous decision-making with onboard control and collision evasion
[112]	Autonomous UAVs with central command influence	Operating Control Unit (OCU)	Demonstrates how UAVs take local actions while receiving high-level commands
[113]	UAV autonomy in complex environments	Cooperative control	Explores local decision-making and coordination in complex environments through onboard sensors
[114]	Local execution and central coordination in multi-agent systems	Local bidding strategies	Improves scalability and reduces computational cost by enabling agents to bid for locally relevant tasks

TABLE III
SURVEY FOR TASK MANAGEMENT AND DYNAMIC ALLOCATION

C. Task Management and Dynamic Allocation

The Task Management and Dynamic Allocation module plays a crucial role in ensuring UAV swarms can efficiently allocate tasks and adapt to changing mission environments. As shown in Table 3, which surveys the relevant works, various approaches focus on dynamic task assignment, adaptive scheduling, and real-time resource optimization. For instance, [88] employs a genetic algorithm for dynamic task allocation and trajectory optimization, while [92] explores real-time task reallocation using an improved Contract Net Protocol (CNP).

Key insights from these works show a trend toward the integration of decentralized decision-making and multi-agent coordination. Papers like [105] highlight the adaptability of Binary Wolf Pack Algorithms for real-time task allocation in dynamic environments, while [108] discusses the importance of human-machine collaboration in uncertain conditions. The overall trend emphasizes the use of AI-driven algorithms, such as reinforcement learning and auction-based task allocation, to enhance the autonomy, efficiency, and adaptability of UAV swarms in complex, unpredictable environments.

Citation	Research Focus	Methodology	Significance/Innovation
[115]	Path planning and dynamic obstacle avoidance	Deep reinforcement learning (SAC)	real-time path planning and obstacle avoidance with SAC and prioritized experience replay
[116]	Autonomous navigation with partial observability	Reinforcement learning	Achieves over 85% success rate in autonomous navigation through reinforcement learning
[117]	Real-time obstacle avoidance for mobile robots	Q-learning	Utilizes Q-learning for effective path planning and dynamic obstacle avoidance
[118]	Autonomous navigation and obstacle avoidance	Double Deep Q-Learning and Faster R-CNN	Efficient autonomous navigation through a hybrid model of supervised and reinforcement learning
[119]	Navigation and obstacle avoidance in UAVs	Vision and LIDAR fusion	Combines vision-based obstacle estimation and LIDAR for effective collision avoidance
[120]	Object detection in ground navigation	Vision and radar data fusion	Enhances obstacle detection in low visibility environments using sensor fusion
[121]	Autonomous vehicle navigation in urban environments	LIDAR and laser rangefinder fusion	Improves tracking and collision avoidance using multisensor fusion
[122]	Obstacle detection through vegetation	Imaging radar and LIDAR	Enhances navigation by detecting obstacles hidden by vegetation
[123]	Off-road navigation with obstacle detection	Stereo-vision and laser-rangefinder fusion	Improves obstacle detection and maneuvering in off-road environments through sensor fusion
[124]	Decentralized flocking guidance for UAVs	Adaptive Cucker-Smale model	Enhances flocking performance by addressing command conflicts in hybrid control
[125]	Autonomous flocking control in UAV networks	Swarm intelligence	Energy-efficient flocking control for collaborative decision-making in dynamic environments
[126]	Collision-free flocking for UAVs	Multi-agent deep reinforcement learning (MADDPG)	Uses attention-based MADDPG for scalable and collision-free UAV flocking
[127]	Location sharing in multi-UAV systems	Multi-token circulation protocol	Improves UAV communication using Flying Ad Hoc Networks (FANETs)
[128]	Autonomous flight coordination for UAVs	Vehicle-to-vehicle (V2V) communication	Enhances UAV safety and efficiency through V2V communication for collision avoidance
[129]	Decentralized UAV communication for network connectivity	Tree-based overlay network	Balances coverage and connectivity in UAV fleets during surveillance missions
[130]	UAV-aided decentralized learning	UAV mesh networks	Improves learning convergence and network connectivity in decentralized mesh networks
[131]	Multi-UAV communication in mesh networks	Wireless Mesh Network (WMN) with AES/Blowfish encryption	Ensures secure and reliable UAV communication using a decentralized mesh network
[132]	Dynamic task reassignment in multi-UAV systems	Phased coordinated task allocation	Ensures efficient real-time task reassignment in response to changing mission conditions
[133]	Real-time task allocation for UAV swarms	Auction-based mechanism (NECTAR)	Improves adaptability and performance through dynamic task reassignment
[134]	Real-time target allocation for UAV swarms	Extended CBBA algorithm (ECBBA)	Enhances efficiency and adaptability in real-time task reallocation during dynamic environments
[135]	Efficient obstacle detection and data protection	Bee and ant-inspired collective intelligence	Improves UAV swarm efficiency in obstacle detection using bio-inspired algorithms
[136]	Decentralized decision-making in multi-agent systems	Swarm intelligence	Develops adaptive decentralized systems using local communication for collective decision-making
[137]	Hierarchical control for UAV teams	Layered control architecture	Supports distributed collaborative control for heterogeneous UAV systems
[138]	Self-organized UAV flocking	Lennard-Jones potential function	Enables UAV flocking without alignment control, improving cohesion and collision avoidance
[139]	Object classification and swarm coordination	Decentralized behavior model	UAVs share object classification data, leading to collective swarm responses
[140]	Decentralized decision-making for UAV systems	Consensus protocols and model predictive control	Achieves coordinated decision-making through decentralized control in UAV missions
[141]	Swarm control with optimal graph partitioning	Multi-agent containment algorithm	Reduces communication redundancy and enhances stable formation control through optimal rigid graph-based coordination

TABLE IV
SURVEY FOR AUTONOMOUS LOCAL EXECUTION

D. Autonomous Local Execution

The Autonomous Local Sensing and Execution module allows UAVs to make independent decisions based on their local environment while maintaining synchronization with global mission objectives. Table 4 provides a comprehensive survey of works that explore technologies related to local sensing, real-time decision-making, and swarm intelligence for UAVs. Key papers such as [115] and [119] emphasize the role of sensor fusion—integrating data from sources like LIDAR and cameras—to enable real-time obstacle avoidance and adaptive navigation. Moreover, [138] and [124] demonstrate how flocking algorithms allow UAVs to autonomously coordinate and optimize flight paths in response to environmental changes.

Overall, the key insights reveal a strong focus on decentralized decision-making and collaborative execution through local interactions. Papers like [126] leverage deep reinforcement learning for collision-free, autonomous navigation, highlighting how UAVs can balance local autonomy with global directives. Additionally, studies like [141] show how optimal graph partitioning enhances coordination and communication, leading to emergent swarm behaviors. These trends indicate that advancements in local sensing, real-time decision-making, and swarm intelligence are essential for improving UAV swarm adaptability and efficiency in complex, dynamic environments.

VI. Challenges and Future Directions

Challenges and Future Directions The concept of a fully realized UAV swarm hive mind remains in its nascent stages. While individual technologies show promise for specific components of the architecture, the integration of these technologies into a cohesive, fully operational hive mind has not yet been achieved. The following are the key challenges and future directions that can guide further research and development in this area:

1. Integration of Large Language Models (LLMs) for Decision-Making LLMs offer promising opportunities for improving the strategic coordination and decision-making capabilities of UAV swarms. While LLMs have shown efficacy in natural language processing and real-time strategic thinking, integrating these models into the hive mind architecture requires addressing scalability and real-time processing limitations. Future work should explore how LLMs can be leveraged for high-level, centralized decision-making, where they can process complex instructions and provide UAVs with nuanced, adaptive mission strategies.

2. Agent-Based Control Mechanisms Agent-based systems have demonstrated potential for decentralized autonomy, allowing UAVs to execute local tasks independently while maintaining a degree of coordination with the swarm. However, achieving seamless integration between centralized strategic control and decentralized agent autonomy remains a challenge. Future research should focus on enhancing hybrid control models, where autonomous UAV agents are capable of executing local tasks based on global knowledge provided by centralized systems while dynamically interacting with each other to adjust to evolving conditions.

3. Blockchain for Secure and Decentralized Collective Knowledge Networks A significant challenge in implementing a hive mind for UAV swarms lies in ensuring secure, scalable, and decentralized knowledge sharing. Blockchain technology, with its ability to create immutable, distributed ledgers, presents a promising solution for maintaining a secure collective knowledge network. However, the computational overhead and energy costs associated with blockchain implementation in UAVs need to be addressed. Future work should explore lightweight blockchain protocols and alternative distributed ledger technologies to enable efficient, real-time knowledge sharing within UAV swarms without compromising security or performance.

4. Real-Time Collective Learning and Adaptation Current swarm intelligence systems often struggle with real-time learning and adaptation to dynamic environments. Future research should investigate the use of multi-agent reinforcement learning (MARL) and continuous learning models to enable UAV swarms to collaboratively improve their behavior over time. This approach would allow the swarm to autonomously refine its strategies and tactics based on mission feedback, without requiring human intervention.

5. Modular and Scalable Hive Mind Framework The proposed hive mind architecture must remain flexible and scalable, accommodating advancements in individual modules without requiring a complete overhaul of the system. Developing a modular architecture where new technologies can be integrated seamlessly is crucial for the future development of UAV swarm systems. Future research should emphasize creating adaptable frameworks that allow for the integration of emerging technologies like quantum computing or advanced AI-driven decision-making.

6. Cross-Disciplinary Collaboration and Standardization Developing a full hive mind system will require collaboration across multiple disciplines, including robotics, AI, communications, and security. There is a need for standardized protocols and frameworks to ensure that different technologies can work together cohesively. Future work should focus on creating cross-disciplinary platforms for research and development, fostering collaboration among academia, industry, and government to accelerate the realization of a fully operational hive mind.

While this paper provides a comprehensive survey of existing technologies and offers a flexible framework for UAV hive minds, the implementation of specific mathematical models, simulations, and performance evaluations will be a key focus of future research. These next steps will serve to validate the architecture and address the real-world challenges identified in this survey. Many technologies exist to enable components of the hive mind architecture, integrating these technologies into a unified system presents substantial challenges. Future research should focus on leveraging LLMs and agent-based systems for decision-making and control, utilizing blockchain for secure and decentralized knowledge sharing, and ensuring the architecture remains modular and scalable. The path toward a fully realized UAV swarm hive mind is complex, but with continued innovation, its potential can be unlocked.

VII. Conclusion

In this paper, we formalized the concept of a UAV swarm hive mind by proposing a flexible, modular framework. This framework integrates centralized cognitive control with decentralized execution, allowing UAVs to function as a cohesive, intelligent system. Each module of the framework, such as task management, collective knowledge sharing, and autonomous execution, has been aligned with existing technologies that contribute to the realization of this architecture.

While a complete hive mind system has not yet been fully realized, our survey of technologies demonstrates that components such as blockchain for secure collective knowledge sharing and large language models for decision-making hold significant promise. These technologies, combined with agent-based control mechanisms, can lay the foundation for more adaptive, scalable, and secure UAV swarm systems.

The formalization of this framework and the identification of core technologies provide a structured path for future research, guiding the development of comprehensive UAV swarm hive minds that can handle complex, dynamic environments autonomously and efficiently.

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