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REVIEW

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Computational offloading into UAV swarm networks: a systematic literature review

Asrar Ahmed Baktayan[1*], Ammar Thabit Zahary[1], Axel Sikora[2] and Dominik Welte[2]

*Correspondence: baktayanasrar@gmail.com

[1] Department of Information Technology, Faculty of Computing and Information Technology, Sana'a University, Sanaa, Yemen
[2] Institute of Reliable Embedded Systems and Communication Electronics (ivESK), Offenburg University of Applied Sciences, 77652 Offenburg, Germany

Abstract

Unmanned Aerial Vehicle (UAV) swarms have emerged as a promising technology for various applications, such as delivery, surveillance, and infrastructure inspection. An additional feature of deploying large UAV swarms is their use in mobile offloading networking. At the same time, this implies a key challenge in the efficient management of the computational and networking requirements for these offloading processes. This paper aims to fill this gap through a systematic literature review (SLR) analysing the research on distributed task offloading in UAV swarms. We conducted a systematic search of major scientific databases to identify relevant literature published between 2019 and 2023. A total of 63 papers were selected through a multistage screening process and their key contributions. This SLR aims to provide the current state of research on UAV swarm task offloading, including considerations for computation offloading, the role of UAV swarms, different aspects of UAV swarms, the number of UAVs in swarms impacting performance, and open issues. Our review also highlights UAV swarm offloading in various domains and discusses the challenges and limitations that must be addressed to ensure the widespread adoption of this technology. We outline the future research directions and potential applications of UAV swarm offloading, including its integration with other technologies.

Keywords: Internet of drones (IoD), UAV swarm, Computation offloading, Mobile edge computing (MEC), Systematic literature review (SLR)

1 Introduction

Unmanned Aerial Vehicles (UAVs), commonly known as drones, have emerged as transformative technologies with a wide range of applications, including surveillance, delivery, and disaster response [1] [2]. The increasing capabilities and affordability of UAVs have led to a growing interest in using UAV swarms for various tasks. A UAV swarm is well suited for monitoring large areas or facilities via cameras and sensors, as the coordinated group of drones can be rapidly deployed to observe wide regions from different angles and vantage points. UAVs can split tasks such as image capture, audio recording, chemical detection, or other sensor measurements across a swarm in a distributed manner based on proximity to events or locations of interest [3].

Mobile edge computing (MEC) servers are deployed in various locations, such as cellular base stations, aggregation points, customer premises, wireless Access Points (Aps), or even UAVs. These servers play a crucial role in processing, analysing, and storing latency-sensitive or location-aware data [4]. By being located close to the source of data generation, MEC servers offer several benefits, such as lower latency, availability even during cloud or internet outages, and an improved user experience. This is particularly advantageous for applications involving Augmented Reality (AR), Virtual Reality (VR), the Internet of Things (IoT), and video analytics [5].

A UAV swarm refers to a group of UAVs that operate collaboratively and autonomously without direct human control in a coordinated manner to achieve a common goal [6]. These swarms can consist of a few drones to thousands of drones, and they operate with limited human control or intervention. UAV swarm architectures can be categorized as mesh-based, star-based, cluster-based or hybrid architectures [7]. A mesh architecture enables fully decentralized control as each UAV operates as a node in an ad hoc wireless mesh network, distributing information across the swarm through multi-hop routing [8]. In a star architecture, UAVs connect directly to a central control node through long-range communication, allowing centralized coordination but introducing a single point of failure. Cluster-based architectures involve UAVs self-organizing into local clusters led by a cluster head for intra-cluster tasks, while also utilizing the benefits of a global mesh network for inter-cluster communication. Hybrid architectures seamlessly combine elements from two or more models, such as a central server that coordinates multiple swarms and employs a mesh formation, providing flexibility to optimize architectures for different mission requirements [9].

With advancements in battery, processor, and wireless technologies, UAVs are being increasingly deployed for various applications across several domains. However, the resource constraints of UAV platforms pose significant challenges for the onboard execution of computationally intensive and latency-critical tasks. Offloading partial or complete workloads from resource-constrained IoTs or drones to powerful edge/cloud servers is a promising solution [10]. However, optimizing the offloading process in UAV environments involves addressing the unique challenges arising from intermittent connectivity, high mobility, and security vulnerabilities [11]. Several techniques have been proposed that focus on minimizing the execution latency and cost of developing UAVs such as MEC [12] while maximizing energy efficiency and accounting for factors such as varying wireless channels, dynamic trajectories (by using differential evolution and Reinforcement Learning) [13], and location privacy (by developed algorithms) [14]. Offloading tasks to UAVs can reduce energy consumption and extend the battery life of the devices. UAVs can also provide high-performance computing capabilities, enabling the execution of complex tasks that may not be feasible on resource-constrained devices (through the developed grouping and role division algorithms) [15].

UAV swarm offloading involves the use of multiple UAVs to collaboratively offload data from a congested terrestrial network or to perform computation-intensive tasks. This approach can significantly improve the efficiency and reliability of wireless communication and computational systems [16]. One of the key benefits of UAV swarm offloading is that it can alleviate network congestion. In areas with a high demand for data, such as densely populated urban centres or large-scale events, networks can become overloaded, leading to slow data transfer speeds and decreased connections. It is possible to distribute the load more evenly and improve the overall network performance [17].

Another advantage of UAV swarm offloading is that it enables more efficient computations. Many modern applications require a significant amount of computational power, which is difficult to provide in resource-constrained environments. By offloading these computationally intensive tasks to a swarm of UAVs, it is possible to distribute the workload and take advantage of the collective processing power of the UAVs. This can lead to faster and more accurate results, as well as reduced energy consumption [18]. However, the implementation of UAV swarm offloading poses several challenges. One of the main challenges is ensuring reliable and secure communication between UAVs and ground networks. This requires the development of advanced communication protocols and algorithms to handle the dynamic nature of UAV networks. Additionally, it is important to consider the energy limitations of UAVs and design efficient algorithms and strategies for offloading data and computational tasks. Finally, regulatory and safety considerations must be considered when deploying UAV swarms for offloading purposes [19].

Overall, UAV swarm offloading has the potential to significantly improve the performance and efficiency of wireless communication and computational systems. By leveraging the collective power of multiple UAVs, it is possible to offload data from congested networks and perform computationally intensive tasks efficiently. However, it is important to carefully consider the associated challenges and trade-offs with this approach to ensure reliable and secure operations.

Figure 1 shows a swarm of UAVs distributed over a 2D area. It provides a visualization of the applications of UAV swarms and how the UAV-MEC system integrates with terrestrial MEC systems. Specifically, this study illustrates that UAV swarms can be employed for various applications and shows the connectivity between UAV-MEC platforms provided by swarms and traditional fixed terrestrial MEC infrastructures. Smaller drones hovering lower are depicted as internet of drones (IoDs), whereas larger drones hovering higher up represent the UAV swarm as MEC. IoD drones collect data, such as images and signals, via their onboard sensors. They offload some computations to a nearby terrestrial MEC or UAV swarm owing to resource constraints. An MEC swarm of UAVs has more powerful onboard processors, storage, and longer-range radios. They perform intensive tasks offloaded from IoDs and terminal devices, such as image analysis

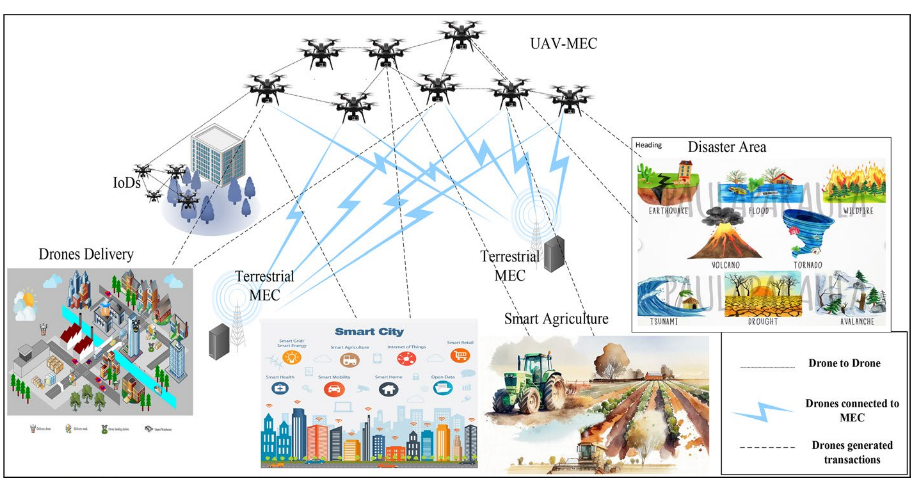

Fig. 1 UAV swarm offloading applications

and data fusion [20]. The thin, solid lines show the wireless connectivity between the IoD and MEC drones. Although research on task offloading from single UAVs or static terrestrial MEC networks is well established, the area of offloading from cooperative UAV swarms is still emerging. To help identify the state of current knowledge and potential future directions in this domain, this paper presents a systematic literature review (SLR) of research related to task offloading into UAV swarm networks. SLR is a type of research paper that synthesizes and analyses the existing research on a particular topic. They are often used to provide a systematic overview of the current state of knowledge on a particular subject and to identify gaps in existing research that need to be addressed. In the case of task offloading in a UAV swarm, an SLR involves a thorough search of the available literature on the topic, including peer-reviewed articles and conference papers. The review then analyses and synthesizes the findings of these studies, identifying patterns, themes, and trends in the research [21].

Coordinating offloading across swarms of collaborating UAVs presents unique challenges owing to intermittent connectivity, resource constraints, and dynamic environmental factors. While prior work has explored various techniques, a systematic review of the state-of-the-art methods is lacking. The contributions of our SLR are in answering the following research questions:

1. What are the relevant considerations for task offloading decisions in UAV swarms? (Sect. 4.1)
2. What are the different UAV swarm roles in task offloading proposed in the literature, and how are they distributed per year? (Sect. 4.2)
3. What factors are common in task offloading decisions in UAV swarm networks such as MEC network, but are different from those in single UAV-MEC or terrestrial MEC networks? (Sect. 4.3)
4. How does the number of UAVs in a swarm affect the performance of tasks offloading to a UAV swarm? (Sect. 4.4)
5. What are the key open issues and challenges in task offloading for UAV swarms basis of the current literature? (Sect. 4.5)

2 Related works

This section summarizes and synthesizes the key related work from available surveys that have considered UAV swarms in recent years. Computational offloading from terminal devices to an edge/cloud infrastructure has been widely studied to optimize resource utilization and user experience. With the emergence of UAV swarm-assisted MEC, offloading paradigms require reexamination under new constraints. Surveys [20–27] have conducted SLR in UAV swarms, whereas [28–30] are comprehensive surveys.

The authors of [22] presented a systematic review of the drone-scheduling problem, which is an essential component of UAV swarm management. The authors discussed various approaches to drone scheduling, including optimization techniques, heuristics, and machine learning methods. They also highlighted the challenges and open research directions in this area. The work [23] provided a systematic review of the use of UAVs for urban traffic monitoring and analysis. The authors discussed various aspects of UAV-based traffic monitoring, including data acquisition, processing, and analysis. They also highlighted the challenges and limitations of UAV-based traffic monitoring and identified future research directions. The authors of [24] presented a systematic review of the use of micro-UAV swarms for industrial applications in indoor environments. The authors discussed various aspects of micro-UAV swarming, including swarm intelligence, communication protocols, and application scenarios. They also highlighted the challenges and open research directions in this area. In [25], the authors presented a systematic review of the optimized routing of UAVs via bioinspired algorithms in flying ad hoc networks (FANETs). The authors explored the application of bioinspired algorithms, such as genetic algorithms, ant colony optimization, and particle swarm optimization, for efficient UAV routing in FANETs. This review discussed the advantages, challenges, and potential research directions of this area. The paper [26] presented a systematic literature review on the topic of the UAV-based internet of vehicles (IoV). The authors analysed existing research on the integration of UAVs and the IoV, including communication protocols, data fusion techniques, and applications. The review highlighted the potential benefits, challenges, and future directions of UAV-based IoV. In [27], a SLR was conducted on the topic of autonomous UAV path planning. The authors reviewed and analysed state-of-the-art techniques and algorithms used for autonomous path planning, including methods based on Artificial Intelligence (AI) and optimization algorithms. The review provided insights into advancements, challenges, and future research directions in this area. The authors [28] explored state-of-the-art techniques, challenges, and perspectives in the field of FANETs, which are networks of UAVs that communicate with each other and ground stations. The authors discussed various aspects of FANETs, including the network architecture, communication protocols, and application scenarios. They also highlighted the challenges and open research directions in this area.

The authors of [29] focused on a comparative analysis of different UAV swarm control methods for unmanned farms. The authors evaluated and compared the various control methods used to coordinate and manage UAV swarms in agricultural applications. The study provided insights into the advantages, limitations, and potential applications of different control methods for UAV swarms in farming. Reference [30] presented a survey on the topic of autonomous multi-UAV wireless networks. The authors focused on Reinforcement Learning (RL)-based approaches for achieving autonomy in UAV networks. The survey explored various RL techniques and their applications in UAV network optimization, resource allocation, and cooperation. The paper provided a comprehensive overview of the current state-of-the-art, challenges, and future directions in this field.

Two comprehensive surveys related to UAV computation offloading were conducted. The first [31] viewed UAVs as IoT devices or mobile edge nodes, but discussed only some technical challenges without focusing on swarms. It also examines the applications and use of AI in edge computing. The second survey [32] considered only UAV swarms used as MEC. The authors focused on implementation considerations for swarms, as well as promising technologies for multi-UAV coordination and resource management. However, our SLR differs in that it covers the various roles that UAV swarms can play in computational offloading systems. It also examines common concerns for UAV swarm deployment and highlights differences compared with offloading via ground edge nodes or single UAVs. In addition, our survey analyses how the number of UAVs affects the offloading process. Finally, while some general surveys exist on UAV swarms and MEC separately or only focus on comprehensive state-of-the-art methods, there has not been a rigorous systematic review specifically focused on computation offloading techniques in the context of UAV swarm networks. To the best of our knowledge, this is the first SLR to analyse an extensive research landscape on a UAV swarm for computational offloading. Table 1 presents a comparison of the survey results of the UAV swarm.

3 Methodology

In this study, our focus is specifically on investigating UAV swarm offloading and its associated issues. It is important to note that we narrowed our scope to only consider issues directly related to task offloading into UAV swarms. The initial search process aimed to identified as many relevant studies as possible. Four popular digital libraries/databases were searched, namely IEEE Xplore, Springer, MDPI, and ScienceDirect. These databases were selected because they index high-quality publications in the fields of computer science, engineering, and technology, which aligns with the topic of this review.

This resulted in an initial pool of 167 articles from four databases (IEEE Explore, MDPI, ScienceDirect, and Springer) from 2019 to 2023. After filtering based on cooperative UAV swarms of 3 or more drones, a final set of 63 primary studies was identified for full analysis as part of the SLR. The PRISMA diagram [33] in Fig. 2, detailing the selection process, clearly depicts the methodology. Citation searching and UCL LIBRARY SERVICES of the included papers were also performed to identify any further relevant studies. We found 13 articles that were added to 50 articles from four databases to complete 63 articles.

The Sankey diagram in Fig. 3 was used to visualize the distribution of the 63 included articles across journals, publishers, and years of publication. The journal box in the leftmost flow shows that most of the articles were published in IEEE. The next largest sources were journals from the MDPI. Moving to the right, the publisher box illustrates most of the included publishers. Finally, the year box on the far right of the diagram maps the number of articles published each year from 2019 to 2023. The majority were published in 2023, demonstrating that this field is still emerging with much work occurring recently.

4 Systematic literature review answers

4.1 Common considerations for task offloading decisions in UAV swarm

This section reports the answer to RQ1 (What are the relevant considerations for task offloading decisions in UAV swarms?). This question highlights the key considerations commonly taken into account when making task offloading decisions across a UAV swarm. Understanding these typical evaluation criteria provides a foundation for then examining how swarms implement task allocation in practical applications. Identifying shared dimensions routinely analysed, such as available resources, latency, energy usage, etc., establishes a standardized framework to facilitate assessing the strengths and weaknesses of different approaches. Several factors are commonly considered for task offloading decisions in UAV swarm networks:

Table 1 Comparison of reviews related to UAV swarms

Refs.	Main objective	Publication year	Security	Review type	Open issue	Offloading	Applications	Covered year
[22]	Drone Scheduling	2022	Not presented	Systematic State-of-the-Art Review	Not presented	Not presented	Delivery of Goods	2006–2021
[23]	Urban Traffic Monitoring	2022	Not presented	Systematic literature review	Not presented	Not presented	Traffic analysis, Traffic monitoring	2010–2022
[24]	Industrial applications in indoor environment	2023	Protect UAVs from hackers and cyber-attacks	Systematic literature review	Joining and leaving micro-UAVs in real time, Dynamic environment conditions, estimate the battery consumption of a micro-UAV	Not presented	Search and Rescue, Indoor and outdoor environments, Surveillance	2011–2021
[25]	Routing of UAVs Using Bio-Inspired Algorithm	2023	Cryptographic algorithms, intrusion detection methods, and reputation-based technique	Systematic literature review	Bio-Inspired Algorithm routing, QoS of FANET, standalone simulator for FANET, link interruption, and FANET	Not presented	Image processing, terrain positioning-assisted underwater route Planning, Wireless Sensor Network (WSN) application,	2000–2022
[26]	UAV-based IoV approaches	2023	Secure data exchange, Physical attacks on drones, and User privacy and security	Systematic literature review	Network device resource limits, Lack of processing power, Network delay, Congestion, Reduced performance, Security and privacy	Not presented	Not presented	2018–2022

Table 1 (continued)

Refs.	Main objective	Publication year	Security	Review type	Open issue	Offloading	Applications	Covered year
[27]	Autonomous Path Planning	2023	Not presented	Systematic literature review	Large and complex Environment, Machine learning-based overheats, Efficient Mapping Techniques, Perception Problems in Cooperative UAVs, Tracking targets with moving obstacles, Remote Sensing and Inspections in unknown environments, and Remote Sensing and Inspections in unknown environments	Not presented	Not Presented	2017–2022
[28]	Flying ad hoc networks	2023	Physical layer security, public safety, and citizen privacy	Systematic literature review	Position issues, efficient QoS, lack of standardization, and regulations	Not presented	Not Presented	2013–2021
[29]	UAV Swarm Control Methods on Unmanned Farms	2023	Not presented	Systematic literature review	Limited agricultural application scenarios, Insufficient levels of intelligence, and Inadequate hardware and software support	Not presented	Application of UAV Swarms in Cultivation	2017–2021
[30]	Reinforcement Learning-Based Approaches	2023	Network security (against jammers and eavesdroppers)	Comprehensive Survey	Multi-Objective Optimization, Resource Allocation and Cooperation, Joint Trajectory Planning, Distributed DRL Framework, Model Training and Implementation, and Security and Privacy Issues	offloading decisions in UAV-assisted MEC system	Application of RL in Multi-UAV network (data collection and sensing, resource allocation for wireless connection, MEC, localization, trajectory planning, network security)	Not mentioned

Table 1 (continued)

Refs.	Main objective	Publication year	Security	Review type	Open issue	Offloading	Applications	Covered year
[31]	Convergence of Edge Computing and AI for UAVs	2022	Improved security and privacy with AI	Comprehensive Survey	Developing Distributed Training Algorithms, Security and Privacy, Resource Allocation, and Real-Time Requirements	UAV-to-server task offloading	Delivery Systems, civil infrastructure inspection, Precision Agriculture, Search and Rescue Operations, Acting as Aerial Wireless BSs, and Drone Light Shows	Not mentioned
[32]	UAV Swarm-Enabled Edge Computing	2022	Enhanced Offloading Security	Comprehensive Survey	Robust Automatic Networking for Large-Scale UAV swarm, Interference Alleviation, Balanced Computation Offloading, Computing Security, Online Path Planning, and Energy-Efficient Multi-UAV Coordination	Multiple Access for Task Offloading	Battle fields, Earth monitoring, Precision agriculture, and Disaster management and good delivery	Not mentioned
This survey	Task offloading in UAV Swarm		Data Confidentiality, Data Integrity, Authentication and Authorization, Network Segmentation	Systematic literature review	Heterogeneity Affects Revenue and Security, Fault tolerance, Scalability, Resource and Communication Constrains, and Dynamic Network Topology	UAV swarm computation offloading	Large-scale data collection and processing, Real-time processing and decision-making, Dynamic network topology, Cooperative computing, and Enhanced coverage and connectivity	2019–2023

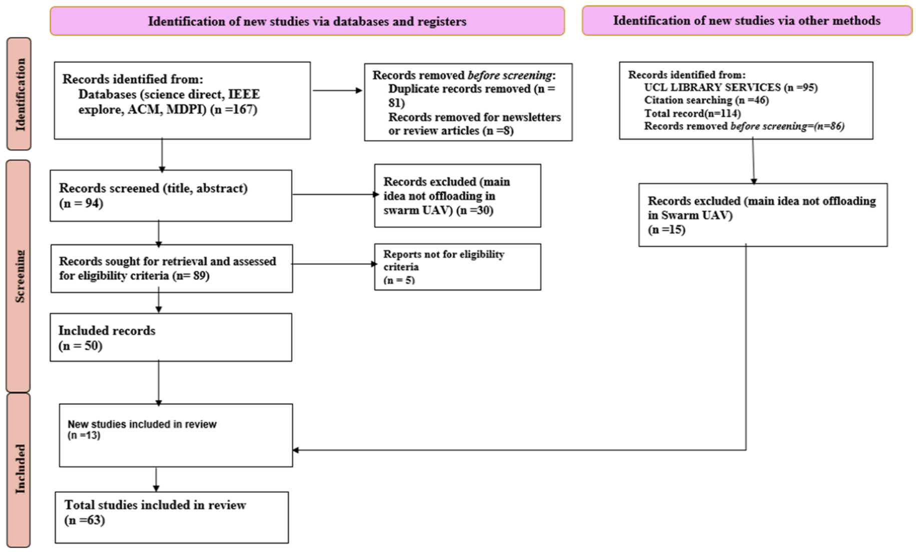

Fig. 2 PRISMA research study databases and inclusion/exclusion factors for article selection

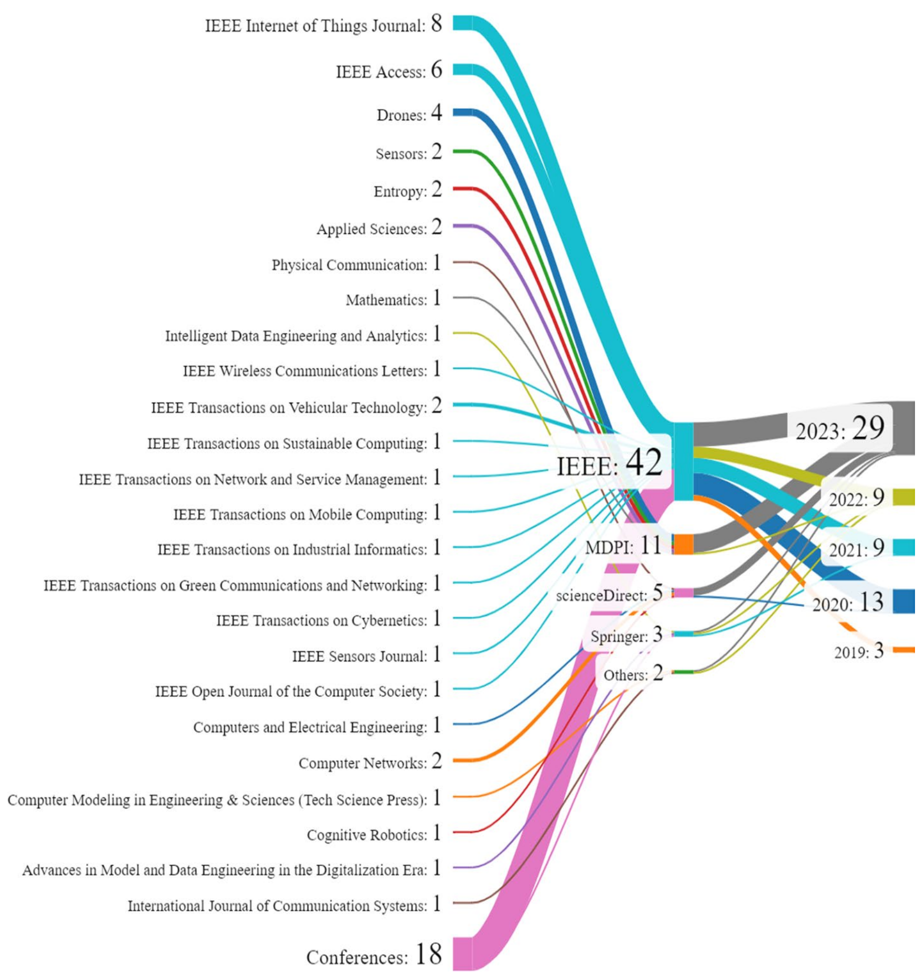

Fig. 3 Sankey diagram showing journals versus publishers vs. year

4.1.1 Task characteristics

Task Priority: The prioritization of different tasks could depend on the dynamic field conditions and policies set for that deployment. While some tasks generally have more immediate importance, what qualifies as a high priority could change depending on real-time events. Additionally, offloading too many tasks at once to edge servers risks overburdening limited resources and delaying responses instead of improving them [21]. The equation that can be used for model latency-based priority for task offloading to UAV-MEC systems is as follows:

$$\text{Priority} = \frac{1}{T_{\text{Deadline}} - T_{\text{Current}}} \tag{1}$$

where $\mathrm{T_{Deadline}}$ is the task deadline, and $\mathrm{T_{Current}}$ is the current time. Tasks closer to their deadline have higher priority [21].

Task Size: Larger tasks may require offloading to MEC servers due to limited onboard resources on UAVs. Computationally intensive tasks such as high-resolution video analysis consume significant amounts of memory and CPU resources from resource-constrained UAVs [34]. Tasks that exceed available onboard storage/computation limits will need to offload portions to MEC servers with higher capabilities [35].

Task Latency Requirements: Latency-sensitive UAV swarm or terminal device tasks may need to be offloaded to MEC servers or another UAV in the swarm to meet strict deadlines [36]. Real-time tasks supporting functions such as tracking, and surveillance cannot accommodate slower onboard processing alone. Latency-sensitive applications requiring low single-digit millisecond responses are better served through UAV swarm offloading for accelerated execution [37].

The total delay depends on the longest delay because of parallel processing of several subtasks among multiple UAV-MEC or ground MEC, which is evaluated as follows [38].:

$$T_{\text{total}} = T_{\text{MEC}} + T_{\text{procc}_{\text{loca}}} + \max_{0 \le i \le I}\{T_{\text{offload}\,U_i 2 U_i + 1}\} \tag{2}$$

where I is the total number of UAVs in a swarm. For UAV to UAV (U2U) partial offloading between nearby UAVs in a swarm, the transmission latency can often be ignored for a few reasons: the distances between nearby UAVs tend to be very short on the order of meters. This results in very low propagation delays. High communication rates are typically possible between nearby devices, due to technologies such as WiFi Direct, Bluetooth, and 5G U2U. This means that data can be transmitted very quickly between devices. The transmissions between nearby devices often occur over line-of-sight, free-space channels with few reflections/scatterings. Since devices process data in parallel, the transmission delays between them are often negligible [39].

Data Requirements: UAV swarm tasks that require access to large datasets or cloud-based services may be offloaded to MEC servers [40]. Tasks that rely on access to back-end databases, cloud services, or large neural network models stored remotely will need MEC connectivity. UAVs often have limited storage capacity, so tasks in which large datasets are fetched large datasets from network locations favour offloading versus local caching/analysing [41].

4.1.2 UAV Characteristics

Computational Capabilities: UAVs with limited computational resources may need to offload tasks to MEC servers for processing [42].

Battery Life: UAVs with low battery levels may need to offload tasks to MEC servers to conserve energy. By offloading tasks, UAVs can reduce their computational workload and minimize battery usage [43, 44].

Communication Capabilities: A swarm of UAVs with limited communication bandwidth or unreliable links may need to offload tasks to MEC servers to improve communication efficiency. However, UAVs may face challenges such as limited communication bandwidth or unreliable links due to interference or signal attenuation [45]. In such cases, offloading tasks to MEC servers can improve communication efficiency by leveraging the servers' higher bandwidth and more stable connections [46].

UAV Mobility: UAVs in a swarm are mobile nodes, and their movement patterns can impact offloading decisions. Their movement patterns and trajectories can impact offloading decisions. For example, UAVs moving at high speeds may experience more frequent handovers with MEC servers, which can introduce additional latency and overhead [47]. Offloading decisions need to consider the mobility patterns and trajectories of UAVs to leverage the proximity of UAVs to task locations [48].

Several mobility models can be used to approximate the movement of nodes in a swarm network. These models include the Gauss-Markov mobility model, Semi Random Circular mobility model, Random Waypoint mobility model, Particle Swarm mobility model, and Paparazzi mobility model. Each of these models has its own advantages, disadvantages, and unique identifying characteristics [49].

The UAV will only move toward its next target when its neighbouring UAVs have reached their own targets. As the number of UAVs in the swarm increases, the probability of having to wait for other UAVs also increases. This waiting time contributes to a nonlinear increase in speed, which is defined as follows:

$$S\text{peedUp(IUAVs)} = \frac{\text{Duration(1UAV)}}{\text{Duration (iUAVs)}} \tag{3}$$

The duration decreases as the number of UAVs in the swarm increases. This means that even though the speed-up is not linear, there is still an improvement in efficiency when more UAVs are added to the swarm [50].

A 3-D Cartesian coordinate system is considered, in which each terminal device $n \in \mathrm{N}$ is in the ground, and its horizon coordinate is given by $wn \triangleq (x_i, y_i)$. The horizontal coordinate of $\mathrm{UAV}_i \in \mathrm{I}$ at slot t is denoted as follows:

$$q_i[t] = (x_i[t], y_i[t]) \tag{4}$$

In slot t, each UAV flies to a new position [51] as follows:

$$\left(q_i[t+1] = \left(x_i[t] + \Delta_{fly} v_i[t]\cos\theta_i[t],\ y_i[t] + \Delta_{fly} v_i[t]\sin\theta_i[t]\right.\right. \tag{5}$$

At a speed of $v_i[t] \in [0, v_i^{\max}]$ and an angle of $\theta_i[t] \in [0{,}2\pi]$. At each slot, the UAV flies for Δ_{fly} seconds and then hovers for the remaining seconds to provide sensing or MEC services to terminal devices [52]. Furthermore, each UAV must maintain a certain distance from other UAVs to avoid collisions. Therefore, for$\forall i, j \in I, i \neq j, \forall t \in T$, we have:

$$d_{i,j}^{UU}(t) = \sqrt{\| q_i(t) - q_j(t)\|^2} \geq d^{\text{safe}} \quad (6)$$

where $d_{i,j}^{UU}$ is the distance between two different UAVs in the swarm, and d^{safe} represents the minimum distance that each UAV must maintain to ensure safe flying [53].

Collaboration and Cooperation: UAVs can collaborate and cooperate to share tasks and resources. This can involve offloading tasks to neighbouring UAVs with more resources or better connectivity, or coordinating task execution among multiple UAVs [54]. This integration requires the development of interoperability mechanisms and protocols to enable seamless task offloading between UAVs and between swarm and MEC servers in heterogeneous networks [55].

Integration with Existing Networks: UAV swarm networks may need to integrate with existing cellular networks or other wireless technologies. Ensuring compatibility and efficient communication between UAVs and MEC servers is crucial for successful offloading [56].

Coordination and Communication: In a swarm of UAVs, coordination and communication among UAVs are crucial for effective task offloading. UAVs need to share information about their tasks, capabilities, and resource availability to make informed offloading decisions [57]. This requires reliable and efficient communication links between UAVs, which can be challenging in dynamic and congested environments [58].

Distributed Decision-Making: In a swarm of UAVs, task offloading decisions are often made in a distributed manner, without relying on a central authority [44]. This requires decentralized algorithms and mechanisms that enable UAVs to collaborate and reach consensus on offloading decisions. Distributed decision-making can be more scalable and robust, but it also introduces additional challenges in terms of coordination and achieving optimal solutions [59].

Heterogeneity: UAV swarms may consist of heterogeneous UAVs with different capabilities, resources, and roles [60]. This heterogeneity needs to be considered when making offloading decisions. For example, UAVs with more powerful processors or better communication links may be better suited for offloading certain tasks [61].

Dynamic Network Topology: In a swarm of UAVs, the network topology is dynamic and constantly changing as the UAVs move and join or leave the swarm [62]. This dynamic topology can impact the performance of offloading and requires adaptive and flexible offloading strategies that can handle changes in network conditions and resource availability [63].

4.1.3 MEC Server characteristics

Servers play a crucial role in enabling task offloading for swarm of UAVs in urban environments. These servers have specific characteristics that determine their effectiveness in handling offloaded tasks. The key characteristics of MEC servers for UAV swarm task offloading are as follows:

Processing capacity: UAV swarm with MEC servers has greater processing capabilities and can handle more offloaded tasks. This capacity is measured in terms of CPU cycles or processing power. Servers with greater processing capacity can efficiently execute complex tasks and algorithms, enabling faster and more efficient task offloading [64].

Storage capacity: MEC servers mounted on UAV swarm or ground station with sufficient storage capacity can store large datasets and intermediate results [65]. This storage capacity allows for efficient data management and processing. Servers with greater storage capacity can handle a greater volume of data, enabling more extensive task offloading [66].

Energy efficiency: Offloading tasks to MECs can help reduce the energy consumption on the swarm of UAVs, but it is important to consider the energy costs associated with data transmission and processing on MEC servers [67]. Energy-efficient MEC servers can optimize their operations to minimize energy consumption while still providing efficient task offloading capabilities [68].

4.1.4 Network conditions

Network conditions play a crucial role in the performance and effectiveness of task offloading in UAV networks. Several factors related to network conditions can impact the task offloading process. The following are some key aspects to consider:

Network latency: A high network latency can impact the performance of UAV swarms offloaded tasks or executing tasks from terminal devices [69]. High network latency can significantly affect the performance of offloaded tasks. This can lead to increased response times and reduced overall efficiency. Minimizing network latency is essential for ensuring real-time and responsive task offloading [70].

Network bandwidth: Limited network bandwidth can constrain the rate of task offloading and data transfer. Limited network bandwidth can pose challenges in task offloading scenarios [71]. Insufficient bandwidth can restrict the rate at which tasks can be offloaded and data can be transferred. Adequate network bandwidth is necessary to support the timely and efficient execution of offloaded tasks [72].

Network reliability: Unreliable network connections can lead to task offloading failures and data loss. [73]. In UAV swarm networks, where devices are constantly moving and changing their positions, maintaining reliable network connections becomes crucial for successful task offloading. Robust network infrastructure and protocols are required to ensure reliable communication between the swarm of UAVs and ground MECs [74].

Interference levels: Interference levels in the network can impact the performance of task offloading to UAV swarm mounted MEC or from UAV swarm to ground MEC [75]. Congested areas with high levels of interference can lead to degraded network performance and hinder the offloading process. It is important to avoid such congested areas when deciding on the location for task offloading. Analysing and monitoring interference levels in real time can help optimize task offloading decisions and ensure efficient data transfer [76].

4.1.5 Security and privacy

Data confidentiality: Sensitive data may need to be encrypted or protected using secure protocols during offloading [77]. This is important for preventing unauthorized access to sensitive information during transmission between the swarm of UAVs and MEC servers and between UAV swarm and terminal devices, as well as during processing and storage on MEC Encryption and secure protocols can help protect data confidentiality and prevent unauthorized disclosure [78].

Data integrity: Mechanisms may be needed to ensure the integrity of data during offloading and processing. This is important to ensure that data are not tampered with or corrupted during transmission or processing [79]. Data integrity mechanisms can detect and correct errors or tampering, ensuring the reliability and accuracy of the data [80].

Authentication and authorization: Appropriate mechanisms should be in place to authenticate and authorize swarm of UAVs, terminal devices, and MEC servers involved in task offloading [81]. This is important for preventing unauthorized access to MECs and to ensuring that only the authorized swarm of UAVs can offload tasks to MEC servers or that terminal devices can offload to the UAV swarm. Authentication and authorization mechanisms can verify the identity of UAVs and MEC servers and grant or deny access accordingly [82]. In regard to authentication and authorization, a challenge arises when dealing with UAV swarm systems from different vendors. The issue is that securing links and protocols may vary, making the task of ensuring security more complex.

Network segmentation: Implementing network segmentation involves dividing a network into smaller, isolated segments. This enhances security by limiting access to sensitive data. By compartmentalizing data centre networks and employing strict access controls and firewalls, networks can protect critical information from unauthorized access [44]. Artificial Intelligence (AI) and Machine Learning (ML) can enhance the identification of anomalies and potential threats, enabling proactive threat mitigation [83]. Additionally, software-defined networking (SDN) allows for dynamic network segmentation, making it simpler to deploy and manage isolated network segments to enhance security [84]. Blockchain can offer decentralized and tamper-resistant solutions for data centre communication networks [85].

4.1.6 Cost and pricing

The cost of offloading tasks to MEC servers or MEC mounted in UAV swarms may be a factor in the offloading decision. MECs may charge a swarm of UAVs (IoDs) or terminal devices for offloading services, and these costs can vary depending on the MEC provider and the pricing model used [86, 87]. UAV swarm operators need to consider the cost of offloading when making offloading decisions, especially for tasks that require extensive processing or data transfer [88, 89]. While various pricing models have been proposed for computational task offloading in UAV swarm networks, the literature lacks research on dynamic pricing schemes specifically for UAV swarm computation offloading. Most works assume a single UAV provider rather than addressing the additional challenges of a multi-vendor UAV environment. There remains an opportunity to investigate dynamic pricing mechanisms that can optimize resource allocation and task distribution across swarms comprising UAVs from different operators [90]. This would need to account for the distributed and autonomous nature of the network as well as uncertainties introduced by the unpredictable mobility of multiple independent UAV collectives. Consequently, there is still a gap in revenue sharing when UAV swarms are not all from one operator or when MEC systems are from multiple vendors. This means that the current revenue sharing models may not adequately address the complexities and challenges that arise when multiple operators or vendors are involved in the deployment and operation of UAV swarms and MEC systems. Table 2 compares common considerations of UAV swarm task offloading.

Table 2 compares common factors considered in the literature for UAV swarm task offloading. However, several limitations remain, task and network characteristics can be difficult to accurately predict due to dynamic conditions, UAV topology changes introduce uncertainty into coordination, MEC models neglect infrastructure variability, environmental factors are unpredictable, security increases overhead and complexity for decentralized systems, and cost feedback may lag for large deployments. Most research also focuses individually on single objective solutions [21, 44] rather than multi-objectives solutions such as [71]. Self-organizing mechanisms may better handle topology dynamism [42]. Balancing multi-objectives under practical limitations remain challenging. Offline optimization also requires testing under real stochastic execution environments. Additionally, proposed methods typically consider homogeneous systems for tractability, but diversities in nodes and workloads may degrade performance. The scalability of techniques for industry scale deployments with thousands of nodes is untested.

4.1.7 Open issues related to RQ1

1. Resource constraints:

   Models assume unlimited resources but constraints such as energy, and bandwidth impact feasibility require investigation.
2. Dynamic topology:
   Unpredictable topology changes affect coordination, but approaches typically assume static settings.
3. Fault tolerance:
   The dependency on wirelessly exposed vulnerabilities but resilience to failures is underexplored.
4. Security complexity with heterogeneity:
   The mix of devices from multiple vendors introduces interoperability challenges for access controls.
5. Inaccurate Price with Heterogeneity:
   Cost models do not capture variations in pricing due to diverse node capabilities.

4.2 Role of UAV swarm for task offloading

This section reports the answer to RQ2 (What are the different UAV swarm roles in task offloading proposed in the literature, and how are they distributed per year?). Understanding the evolving roles of UAV swarms in task offloading is crucial as it reflects the rapid advancements in both UAV technology and edge computing. By examining these roles and their distribution over time, we can identify trends, challenges, and opportunities in the field. This analysis provides insight not only into the current state of UAV swarm applications in task offloading, but also predicts future directions and potential breakthroughs. Moreover, this question sets the foundation for our subsequent research questions by establishing the context of UAV swarm capabilities and their development

Table 2 Comparison between common considerations of task offloading in UAV swarm networks

No.	Consideration	Description	Optimization objective	Key factor considered	Limitations
1	Task Characteristics	Attributes of the task itself (e.g. size, priority, latency)	Match tasks to appropriate execution MECs	Task priority, size, latency requirements, data/resource needs	Task attributes may not always be accurately known
2	UAV Characteristics	Attributes of individual UAVs (e.g. resources, energy, mobility, Task Collaboration)	Maximize UAV resource utilization	Available resources, battery levels, mobility patterns, capabilities	Dynamic topology introduces uncertainty, and coordination overhead grows with numbers
3	MEC Server Characteristics	Attributes of edge servers (e.g. resources, location, energy efficiency)	Maximize server resource utilization	Available resources, location, energy consumption	Static attributes don't capture dynamism, and single point of failure
4	Network Conditions	Attributes of wireless environment (e.g. latency, bandwidth, reliability)	Ensure reliable task execution	Latency, bandwidth, reliability, interference levels	Environment conditions are uncertain and unpredictable
5	Security and Privacy	Attributes for data protection (e.g. confidentiality, integrity, authentication)	Enhance security of offloaded tasks	Confidentiality, integrity, authentication, segmentation	Security adds computational overhead, and complexity with heterogeneity
6	Cost and Pricing	Attributes related to cost (e.g. resource/transfer costs, dynamic pricing)	Minimize economic cost of offloading	Resource/transfer costs, dynamic pricing incentives	Delayed/inaccurate pricing feedback for large or heterogeneous network

timeline. UAV swarms can play an important role in distributed task offloading systems, either as IoD devices that generate computational tasks or as MEC platforms themselves [16]. When functioning as IoDs with resource constraints, a UAV swarm collects sensed data and generates tasks that need to be processed. However, when a UAV swarm collaboratively acts as a MEC platform through distributed computation and resource sharing among its members, it can provide low-latency localized processing of tasks in a scalable manner [91, 92]. The swarm of UAVs in hybrid role task offloading roles combines aspects of IoDs and aerial mobile edges.

4.2.1 UAV internet of drones

Swarm of UAVs, commonly known as drones, can be utilized as IoT devices with sensors and cameras onboard for data collection. UAVs can play a crucial role in various applications, including surveillance, monitoring, and data gathering [10]. Multiple drones form a swarm/cluster and connect with each other via short-range wireless protocols such as WiFi-Direct and Bluetooth to establish an aerial ad hoc network [93], where UAVs connect to a Base Station (BS) through intermediate devices known as cluster heads. In certain situations, multiple UAVs collaborate to serve a specific region, thereby resulting in a swarm of UAVs. In practical scenarios, multiple stakeholders combine to form a UAV swarm configuration and provide surveillance services. In [93], the authors proposed a pricing Stackelberg game involving UAVs, cluster heads, and BSs by defining their behavioural utilities. By utilizing PSO for each entity's utility functions, an optimal pricing strategy is created for each entity to maximize its profits. They coordinated their flight paths, shared sensor data, and performed tasks in a decentralized peer-to-peer manner within a drone swarm network.

After UAV i perceives the task data, it may process the tasks locally. The local execution time can be computed as

$$t_{i,k}^{\mathrm{loc}} = \frac{c_{i,k}}{\lambda_i} \tag{7}$$

where λ_i indicates the computational capability of UAV i and $c_{i,,\kappa}$ denotes the number CPU needed to complete task κ. There is more than one UAV that will offload tasks to the same MEC server in the same time period. The distance between UAV i and MEC server m is:

$$d_{i,m} = \sqrt{dv_{i,m}^2 + dh_{i,m}^2} \tag{8}$$

where $dv_{i,m}$ and $dh_{i,m}$, indicate the vertical and horizontal distances between the UAV i and MEC server m, respectively. Then the transmission time $l_{i,k,m}^{tr}$ of the task data for UAV i can be represented as

$$l_{i,k,m}^{tr} = \frac{d_{i,k}}{\zeta_{i,k}} \tag{9}$$

$\zeta_{i,k}$ is the achieved data transmission rate. After the task data are transmitted to the MEC server m, the data processing time $l_{i,k,m}^{exe}$ on the MEC server m can be represented as follows:

$$l_{i,k,m}^{exe} = \frac{\mathrm{c_{m,k}}}{\lambda_{\mathrm{m}}} \tag{10}$$

in which λ_m denotes the computational capability of MEC server m. Therefore, the total time consumed by UAV i during offloading is expressed as [51]:

$$l_{i,k}^{MEC} = l_{i,k,m}^{tr} + l_{i,k,m}^{exe} \tag{11}$$

4.2.2 UAV aerial mobile edge computing (MEC)

The UAV swarm can move around in the network, providing computational resources to different locations, as needed. This mobility can be advantageous in scenarios where the demand for computational resources varies across different areas [94]. Drones act as flying access points or edge nodes that provide on-the-wing computation and networking to other drones in the swarm or to any terminal device. Selected drones with higher capabilities take on edge-computing roles to excuse tasks from others and process data collaboratively [95]. The authors of [34] presented a network architecture that involves multiple Low Earth Orbit (LEO) satellites, UAVs, and IoT devices. The UAV acts as an intermediary device between LEO satellites and IoT devices, collecting resource information from the satellites and task information from the devices to offload ground tasks to either the UAV or LEO satellites. The optimization problem was then defined as a Markov decision process (MDP), and a deep deterministic policy gradient and long short-term memory (DDPG-LSTM)-based algorithm was developed to address the issue of task offloading and resource allocation. This approach aimed to improve the efficiency and reliability of the network by offloading tasks to the most suitable node based on the current resource availability and task requirements.

The UAV servers utilize OFDMA or NOMA technology to serve the TDs, which is utilized to avoid transmission interference between multiple TDs. Due to the flight altitude of the UAVs, there is a good line-of-sight link between the UAVs and TDs. Thus, the channel between the UAVs and terminal devices is modelled as a line-of-sight channel model. When the computational tasks are offloaded to the UAV servers via the Ground-to-Air (G2A) channel, the required transmission time can be formulated as

$$t_{i,k}^{tr}(t) = \frac{D_k}{V_{i,k}^{up}(t)} \tag{12}$$

where $V_{i,k}^{up}(t)$ is the uplink transmission rate, and the D_k denotes the task size of the TD.

When UAV_i receives an offloading task from the TD, the computation time $t_{i,k}^{com}(t)$ caused by UAV_i processing the task is given by

$$t_{i,k}^{\mathrm{com}}(t) = \frac{D_k C_i}{v_i} \tag{13}$$

where c_i and v_i denote the number of CPU cycles and computational capability of UAV_i, respectively.

Since the downlink delay is negligible in comparison with the uplink delay, it is ignored when calculating the total transmission latency for offloading a computational task. The latency of UAV-MEC consists mainly of transmission latency and computation latency

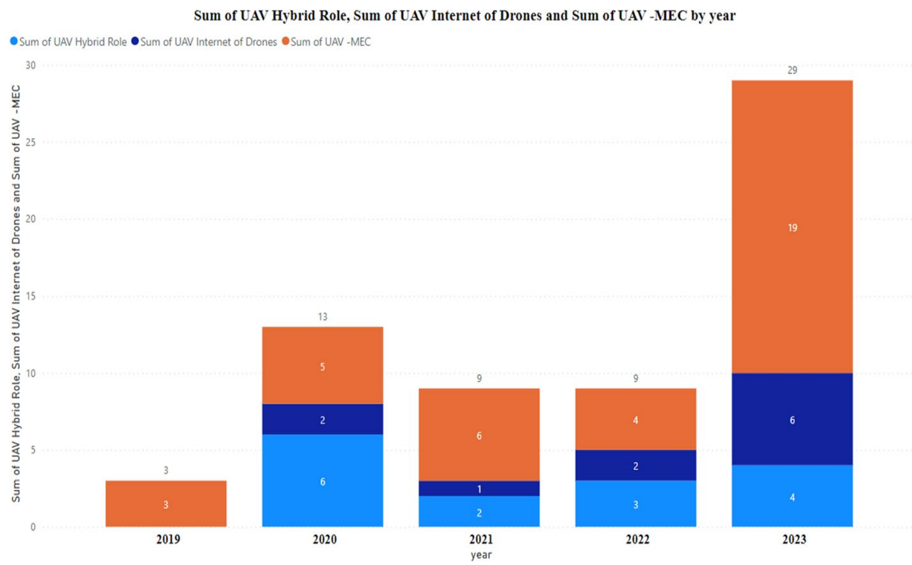

Fig. 4 UAV swarm offloading role publication trends

$$t_i^{all}(t) = t_{i,k}^{tr}(t) + t_{i,k}^{\text{com}}(t) \tag{14}$$

4.2.3 UAV hybrid role

Drones utilize swarm networking for local onboard coordination and task sharing. Computation-intensive or delay-sensitive tasks are pushed to nearby aerial edge drone nodes. In scenarios where multiple UAVs are deployed, data can be offloaded from one UAV that collected data to another. This can be achieved through wireless communication protocols such as Wi-Fi or Bluetooth [21]. UAVs can also execute tasks locally, and the UAV swarm can then process and utilize the collected offloaded data for various applications [96]. In the context of data collection, a UAV swarm [81] is utilized to gather information from various sources, such as sensors or IoT devices, in a distributed manner. This allows for efficient and comprehensive data collection over a wide area. On the other hand, the UAV swarm also serves as an MEC platform, enabling edge computing capabilities. By leveraging distributed neural networks, the UAV swarm can perform fast inference tasks at the edge, reducing latency and improving real-time decision-making capabilities. This hybrid approach combines the advantages of both data collection and edge computing, enabling the UAV swarm to efficiently collect and process data in a distributed manner.

Figure 4 illustrates the focus on UAV swarm roles of task offloading in the period from 2019 to 2023, which is likely due to the potential benefits of MEC in improving the performance of mobile applications and services. MECs can provide low-latency and high-bandwidth connectivity, which is essential for many applications, such as augmented reality, virtual reality, and real-time video streaming. The trend toward UAV swarms applying a hybrid role in 2023, as shown in Fig. 4, is maximized due to the growing recognition of the benefits of this approach.

When the objective is to reduce latency for task offloading between small drones (IoDs) and large drones, the approach is to first compare the total latency of the two options on a per-task basis. For each task, the latency of performing the computation locally on the IoDs is calculated. Then, the latency of transmitting the data from the small drone to a large drone for remote processing is estimated. This involves assessing both the transmission delay and processing time if offloading to the large drone. Latency-based decision-making can be described as follows:

$$t_c = \left(t_{i,k}{}^{\mathrm{com}} + t_{i,k}^{tr}\right) - t_{j,k}^{loc} \tag{15}$$

where t_c is the latency comparison. If the latency of performing the computation locally on the small IoD drone itself is less than the total latency of transmitting the raw data to a large drone and then processing it there, then the IoD drone will choose to execute the task locally. Conversely, if transmitting the data and processing it remotely on a large drone would have lower latency compared to local execution on the IoD drone, then the IoD drone will instead opt to offload the task [97]. Table 3 compares the roles of the UAV swarm in the task offloading process.

The choice of UAV swarm role for task offloading depends on the specific application and network requirements. For applications that require real-time data processing and low latency, a UAV swarm as IoD devices offloading tasks to the MEC may be more suitable. For applications that require low-latency, high-bandwidth communication, a UAV swarm in the MEC role may be more suitable. For applications that require a combination of data collection and computation, a UAV hybrid role may be the best choice. From Table 2 there are more references about UAV swarms as MECs for data offloading than UAV swarms that are working only as IoDs or working in hybrid mode, since MEC has been around for longer and has been widely adopted by mobile network operators and cloud providers. This means that there is a large body of research and development on MEC, including research on task offloading in UAV swarm networks. UAV swarms offer several advantages for MEC, including their mobility, flexibility, and ability to provide coverage in areas where traditional cellular networks are not available. This makes UAV swarms a good choice for deploying MEC servers in remote or underserved areas. However, there is growing interest in these areas, and it is likely that we will see more research and development on hybrid mode UAV swarms in the future.

4.2.4 Open issue related to RQ2

1. Communication constraints:

   Rapidly changing wireless links impact operations. Optimizing role selection given unreliable connectivity during movement requires exploration.
2. Fault tolerance:
   Failure resilience is crucial, but the dependence on wireless links increases vulnerability. Evaluation of the adaptive approaches for maintaining service continuity despite faults is needed.
3. Scalability:

Table 3 UAV swarm role comparison for task offloading

No.	Features	UAV swarm as IoT devices offloading tasks to MEC	UAV swarm as MEC	UAV hybrid role
1	Primary Function	Data collection	Computation	Data collection and computation
2	Offloading Direction	UAVs to ground MEC	Terminal devices to UAVs	UAVs to UAVs or Terminal device to UAV swarm
3	Resource Provision	Data	Computation	Data and computation
4	Processing tasks	Processing IoDs tasks are offloaded to MEC servers for faster and more efficient processing	Processing IoT tasks are performed onboard the UAVs, reducing the latency and bandwidth requirements	Processing IoDs tasks are performed onboard the swarm UAVs, reducing the latency and bandwidth requirements and processing UAV tasks are offloaded to another UAV in UAV swarm
5	Network Architecture	Flying ad hoc network with short-range wireless technologies	Drones as flying access points or edge nodes providing on-the-wing computation	Drones utilize swarm networking for local coordination and task sharing, offloading computation-intensive tasks of IoDs to nearby aerial edge nodes
6	Infrastructure	Cluster heads connect UAVs to ground MEC	UAVs act as edge computing nodes	UAVs act as both data collectors and edge computing nodes
7	Communication	Communication is established between UAV swarm and ground MEC servers using wireless links	Communication is established between UAV swarm and terminal devices using wireless links	Communication is established between UAVs using ad hoc networking protocols and between UAVs and environment (both intra-swarm and external network)
8	Computing resources	Computing resources are provided by ground MEC servers located at the edge of the network	Computing resources are provided by the onboard processors of the UAVs in swarm	Computing resources are provided by the onboard processors of the UAVs or offloaded to other UAVs in swarm
9	Scalability	Scalability is limited by the capacity of the MEC servers and the number of UAVs that can be supported by the network infrastructure	Scalability is achieved through distributed processing and the ability to add more UAVs to the swarm	Scalability is achieved through distributed processing and the ability to add more UAVs to the swarm
10	UAV Energy consumption	Energy consumption of UAV is reduced as processing tasks are offloaded to MEC servers, reducing the load on the UAVs	Energy consumption of UAV swarm is increased as processing tasks are performed onboard the UAVs	Energy consumption of UAV swarm is increased as processing tasks are performed onboard the UAVs
12	Deployment	Deployment requires the installation of MEC servers at the edge of the network and the integration of the UAV swarm with the network infrastructure	Deployment is simpler as swarm of UAVs can operate independently and do not require integration with existing network infrastructure	Deployment is simpler as swarm of UAVs can operate independently and do not require integration with existing network infrastructure
13	Latency	Latency is reduced as processing IoDs tasks are offloaded to ground MEC servers located at the edge of the network	Latency is further reduced as processing terminal devices tasks are performed onboard the UAVs	Latency is reduced better than others as processing IoT and IoDs tasks are performed onboard the UAVs

Table 3 (continued)

No.	Features	UAV swarm as IoT devices offloading tasks to MEC	UAV swarm as MEC	UAV hybrid role
14	Fault tolerance	Fault tolerance is provided by the redundancy of ground MEC servers and the ability to offload tasks to other servers in case of failure	Fault tolerance is provided by the redundancy of UAVs in the swarm and the ability to distribute processing tasks among them	Fault tolerance is provided by the redundancy of UAVs in the swarm and the ability to distribute processing tasks among them
15	Mobility	Affects connectivity and offloading between mobile UAVs and stationery MEC	The UAV swarm can move around in the network, providing computational resources to different locations, as needed. This mobility can be advantageous in scenarios where the demand for computational resources varies across different areas	The UAV swarm can move around in the network, providing computational resources to different locations, as needed. This mobility can be advantageous in scenarios where the demand for computational resources varies across different areas
16	Caching	Not applicable	Caching among swarm members to improve efficiency	Caching among swarm members to improve efficiency
17	Limitation	Limited wireless backhaul bandwidth between drones and ground MEC servers Increased latency compared to local drone processing due to longer communication paths Single point of failure	Coordination overhead increases with number of UAVs for optimal task distribution Limited scalability as complexity grows exponentially with swarm size Mobility effects resource availability uncertainty within dynamically formed groups	Higher message overhead for distributed coordination across multiple swarms Scalability challenges with increasing inter-swarm coordination complexity Resource availability inconsistencies across dynamically interacting swarms
18	References	[16, 60, 71, 87, 89, 98–105]	[15, 21, 34, 36, 40, 44, 45, 55, 57, 62, 65, 67, 69, 77, 79, 106–126]	[42, 47, 54, 64, 73, 75, 81, 127–135]

Validation is needed for techniques for managing gigantic industrial scale fleets that perform hybrid roles with thousands of nodes operating under constraints.

4. Coordination constraints:
   Harmonizing autonomous operations across mixed role combinations introduces complexity. Understanding decentralized coordination at immense scales is an open challenge.

4.3 Differences in UAV swarm offloading from a single UAV or terrestrial MEC

This section reports the answer to RQ3 (What factors are common in task offloading decisions in UAV swarm networks such as MEC, but are different from those in single UAV-MEC or terrestrial MEC?). This question examines how task offloading differs for UAV swarms compared to single UAVs or terrestrial MEC systems. Understanding the distinguishing aspects of swarms provides valuable context when analysing their offloading approaches. While common considerations are shared with other environments, swarms also present unique challenges due to their operational characteristics. Identifying these divergences explains why techniques tailored for other domains may not directly translate and underscores the need for solutions. The key differences in task offloading decisions for UAV swarms compared with other contexts such as single UAV, terrestrial MEC, or cloud computing are as follows:

4.3.1 Distributed decision-making

In a UAV swarm, offloading decisions can be made in a decentralized and cooperative manner. This is because each UAV in the swarm has limited communication and computational resources, and the topology of the network is constantly changing due to the mobility of the UAVs [136]. Therefore, each UAV needs to make offloading decisions based on inputs from multiple peers and local information. For example, a UAV may decide to offload a task to another UAV or to the edge/cloud node, which has more computational resources available [89]. In UAV swarms, task offloading decisions can be based on the proximity of UAVs to the task location. UAVs that are closer to the task can execute the offloaded task, reducing latency and improving response time [137]. This approach is different from ground MEC or cloud computing, where offloading decisions are typically based on factors such as network conditions, computational capabilities, and energy efficiency. UAV swarms operate in dynamic environments, where the task requirements and the availability of resources can change rapidly. The proposed Distributed Neural Network (DNN) in the [138] operation scheme utilized an Improved PSO (IPSO) algorithm to enable efficient offloading of distributed decision-making in UAV-assisted MEC networks. The IPSO algorithm is employed to optimize task allocation and resource scheduling among UAVs and MEC servers, considering factors such as task priorities, UAV capabilities, network conditions, and energy consumption. By leveraging the distributed nature of UAVs and the computational resources of MEC servers, the scheme enables collaborative decision-making and reduces the burden on individual UAVs. The approach improves the overall system performance, reduces latency, and enhances the reliability of decision-making in UAV-assisted MEC networks. The IPSO algorithm facilitates efficient offloading of distributed decision-making tasks, enabling

UAVs and MEC servers to work cooperatively and make optimal decisions in a distributed manner.

4.3.2 Load balancing (UAV swarm cooperation)

In UAV swarms, multiple UAVs work together to accomplish a common goal. Therefore, task offloading decisions need to consider the coordination and collaboration among UAV-MEC servers, which is different from single UAV scenarios [139]. In UAV swarms, tasks can be distributed among multiple UAVs, allowing parallel processing and faster completion of tasks. This is in contrast to single UAV scenarios where a single UAV handles all the tasks. Additionally, the computational load must be distributed smartly among swarm members and edge resources based on their varying capabilities over time [140]. For example, a UAV with more computational resources may be assigned more complex tasks, while a UAV with less computational resources may be assigned simple tasks. This helps to balance the computational load and ensure that all tasks are completed efficiently. The distributed nature of UAV swarms allows for data-centric routing and collaborative task execution at multiple nodes [66]. This means that tasks can be offloaded and executed at different UAVs within the swarm, leveraging their computational capabilities. By distributing the computing load, the overall efficiency and performance of the swarm can be improved [141]. For example, the mission-planning layer in [42] aimed to schedule the mission of UAV swarm in such a way that the total mission cost was minimized. This involved assigning tasks to the UAVs and monitoring their status and completion. Load balancing plays a crucial role in the process by ensuring that tasks are evenly distributed among the UAVs, taking into account factors such as task dependencies, UAV capabilities, and mission constraints.

4.3.3 Energy efficiency

UAV swarms are typically powered by batteries or fuel, so optimizing energy usage is crucial. This includes minimizing energy consumption for tasks, coordination, and offloading across the swarm. By efficiently allocating tasks and coordinating the workload, energy can be conserved, extending the operational time of UAVs [142]. In UAV swarms, energy consumption needs to be optimized across all UAVs to ensure that the swarm can accomplish its mission without running out of power. This means that task offloading decisions must consider the energy consumption of the UAVs and avoid offloading tasks that would drain their batteries too quickly [143]. [122] addressed the challenges of traditional fixed base stations in complex terrains by proposing the use of UAVs as MEC nodes in the air. The goal is to provide additional computation and storage capacity for smart city applications and the industrial IoT. The paper presented a multi-UAV-assisted MEC offloading algorithm that involves global and local path planning controlled by a ground station and onboard computer.

4.3.4 Privacy and security

Task offloading decisions in UAV swarms may involve sharing sensitive data. Therefore, strong mechanisms are required to ensure the secure management of these data [57]. UAV swarms can be vulnerable to security attacks such as eavesdropping or jamming, so task offloading decisions must consider the associated security risks. This includes evaluating the trustworthiness of other UAVs or the ground MEC system before offloading tasks [144]. For example, secure UAV-enabled massive vaccine distribution for the COVID-19 Underlying 6G network is a proposed solution in [104] that aimed to address the challenges of fake vaccine distribution by utilizing UAVs and 6G enhanced Ultra-Reliable Low Latency Communication (6G-eURLLC) technology. The scheme incorporated blockchain technology to ensure secure and transparent vaccine distribution. It involved user registration, vaccine requested, and distribution through a public Solana blockchain [145] setup, which allows scalable transaction rates. The scheme utilized UAV swarms triggered by vaccine requests at production setups to deliver vaccines to nodal centres in real time. Additionally, an intelligent edge offloading scheme is proposed to support UAV coordinates and routing path setups.

4.3.5 Dynamic network topology

Attributes such as the dynamic topology, unpredictable connectivity, and energy/computation constraints of flying nodes need greater consideration. The mobility of UAVs in a swarm introduces unique challenges for task offloading decisions [120]. For instance, the dynamic topology of the network due to the movement of UAVs can result in unpredictable connectivity, which can affect the ability to offload tasks. Additionally, UAV swarms have highly dynamic network topologies, with UAVs joining or leaving the network at any time and rapidly changing the network structure. Task offloading decisions need to be adaptive and responsive to these changing network conditions. This may involve dynamically reassigning tasks, adjusting communication routes, or adapting the offloading strategy based on the current network topology [74]. Airborne computing proposed in [119] is a toolkit that enables UAV-assisted federated computing for sustainable smart cities. It leveraged the capabilities of UAVs to support distributed computing and data processing in smart city dynamic environments. The goal was to enhance the efficiency and sustainability of smart city operations by utilizing the computational power and mobility of UAVs.

4.3.6 Quality of service (QoS) requirements

UAV swarms are often used in mission-critical applications, such as search and rescue operations, where low latency and high reliability are essential for success. Task offloading decisions need to consider the QoS requirements of individual tasks and ensure that they are met while optimizing resource utilization and energy consumption [146]. For example, tasks that require real-time processing may need to be offloaded to UAVs with high computational capabilities, while tasks that can tolerate some delay may be offloaded to UAVs with lower computational capabilities or even to the ground MEC [66]. The proposed approach in [114] utilized multi-agent DRL for joint task offloading and resource allocation in a multi-UAV-enabled IoT edge network. Multiple DRL agents, each representing a UAV, learned to make optimal decisions regarding which tasks to offload and which resources to allocate, considering factors such as task priorities, UAV capabilities, network conditions, and energy consumption. The agents interacted with each other and the environment to learn a cooperative strategy that maximizes the overall system QoS performance. The approach enabled efficient task offloading, reduced communication overhead, and improved resource utilization, resulting in enhanced network performance and QoS for IoT devices.

4.3.7 Heterogeneity

UAVs in a swarm may have different capabilities and resource availability, such as different computational power, memory, energy, and communication range. Task offloading decisions need to consider the heterogeneity of the UAVs and allocate tasks to the most suitable UAVs based on their capabilities and availability [147]. For example, tasks that require high computational power may be offloaded to UAVs with more powerful processors, while tasks that require more memory may be offloaded to UAVs with greater memory capacity [148]. The framework in [60] is a decentralized task offloading algorithm for multi-UAVs operating in U2X (UAV to everything)-assisted heterogeneous networks. DRL is utilized to enable each UAV to learn optimal task offloading decisions based on local observations and interactions with neighbouring UAVs. This decentralized approach eliminates the need for a central controller, making the system more scalable and robust. The framework considered various factors such as UAV capabilities, task requirements, network conditions, and energy consumption to make informed offloading decisions. By offloading tasks to U2X APs or other UAVs with sufficient resources, the framework improves the overall performance of the UAV swarm in terms of task completion time, energy efficiency, and network utilization. Heterogeneity in UAV swarm offloading can pose major challenges when the UAV swarm is not from the same operator and requires inter-working between multiple vendors. This is because different operators and vendors may have varying hardware, software, communication protocols, and operational procedures.

4.3.8 Communication constraints

In UAV swarms, task offloading decisions need to consider the limited communication range. These involve dynamic multi-hop aerial mesh networking between numerous mobile nodes [124], which is vastly more complex than simple point-to-point links for single UAVs or fixed infrastructure [149]. Offloading decisions need to consider the communication overhead and minimize the amount of data transmitted over the network [150]. The authors of [21] proposed a prioritization-based task offloading mechanism for UAV-assisted edge networks that optimizes bandwidth utilization. Without centralized coordination, UAVs cooperatively gather information on current network conditions, tasks queued at edge nodes, and their own bandwidth capabilities. An auction-based distributed algorithm allowed the UAVs to negotiate and determine the priority of different tasks based on latency-criticality, execution status, and data transfer requirements. Higher priority tasks are assigned to UAVs with sufficient available bandwidth to minimize their completion delay [151]. Spatial coordination is needed across multiple UAVs to efficiently share wireless resources, avoid interference, and aggregate bandwidth across different locations [71]. Moreover, on-board computation competes for limited transmission power and antenna space with communication radios on each UAV. Line-of-Sight (LoS) blocking and signal attenuation also occur more often in 3D mobile aerial networks than in 2D ground setups [152]. Offloading decisions should be made to minimize communication overhead and ensure reliable communication between UAVs and

MEC servers or between terminal devices and the UAV swarm [37]. In MEC or cloud computing, communication constraints may be less critical because the communication infrastructure is typically more robust. UAV swarms often operate in environments with limited or unreliable communication links. This can make it difficult to coordinate task offloading decisions among individual UAVs and can also limit the amount of data that can be transferred between the UAVs and the ground MEC and between UAV swarm and terminal devices [31]. The authors of [15] considered task offloading in UAV swarm-based edge computing to involve grouping UAVs into clusters and assigning roles to each UAV within a cluster to optimize task execution and resource utilization. UAVs can be grouped based on their capabilities, locations, and energy levels, while their roles can include data collection, computation, and communication. The grouping and role division enabled efficient task offloading, reduced communication overhead, and improved the overall performance of the UAV swarm in providing edge computing services.

4.3.9 Cost constraints

UAV swarms can be expensive to operate, and the cost of task offloading can be a significant factor in determining the overall cost of swarm's operation. This means that task offloading decisions must consider the cost of offloading tasks to other UAVs, to the ground MEC, or from terminal devices to the UAV swarm [114]. For example, tasks that require high computational power may be offloaded to UAVs with more powerful processors, but this may come at a higher cost in terms of energy consumption and communication overhead. Additionally, the security service pricing model in [93] for UAV swarms using a Stackelberg game approach allowed stakeholders, including the UAV swarm provider, cluster heads, and the base station, to determine optimal pricing strategies that maximize their profits while ensuring that users receive security services at a reasonable price. The approach promoted competition among cluster heads, leading to lower prices for UAVs, and facilitating the development of a sustainable and efficient UAV swarm security service market. Table 3 shows a comparison between using a swarm of UAVs and using either a single UAV or ground-based MEC for the purpose of offloading computational tasks.

4.3.10 Applications

UAV swarms for computational offloading have several unique applications that are different from single UAV or terrestrial MEC applications. Some of these applications include the following:

1. **Large-scale data collection and processing:** UAV swarms can be used for large-scale data collection and processing, such as environmental monitoring [98], disaster response [100], and precision agriculture [129]. Multiple UAVs can cover larger areas and collect more data in a shorter amount of time than single UAVs or terrestrial MEC.
2. **Real-time processing and decision-making**: UAV swarms can be used for real-time processing and decision-making in applications such as search and rescue [54], military operations, and sports events [73]. Multiple UAVs can provide real-time data

and offload computations to edge servers for real-time processing, which is critical for making quick and accurate decisions [153].

3. **Dynamic network topology:** UAV swarms can provide dynamic network topology, which is useful for applications such as enhanced coverage and connectivity in remote or hard-to-reach areas [40], temporary networks [114], ad hoc networks [103], and mobile networks. The UAVs can move to different locations based on the demand for computation and network resources, providing a flexible and adaptable network infrastructure [154].
4. **Cooperative computing:** UAV swarms can be used for cooperative computing, where multiple UAVs work together to solve complex computational tasks. This approach can be useful for applications such as scientific simulations, machine learning [64], and data analytics.
5. **Mapping:** UAV swarms can create high-resolution maps of areas that are difficult to access or too large to map using traditional methods. They can quickly and efficiently gather and process large amounts of data, providing accurate and up-to-date maps [155].

Table 4 shows the comparison between the UAV swarm and single or ground MEC in computation offloading [128].

The majority of existing research on computational offloading in UAV swarm networks tends to focus on optimizing energy consumption [62, 127] and latency [73, 79] related to communication constraints as the primary objectives. Ensuring certain levels of QoS [111, 114] is also a relatively common area of study that receives notable attention. However, other important factors such as fault tolerance, security [81], cost [114] modelling, and heterogeneity [77] have been comparatively less explored and analysed within the literature thus far. Moreover, research has focused more on the theoretical optimization of one objective such as latency ignoring practical economic limitations. Cost analysis requires comprehensive modelling of diverse factors, which increases complexity and validation efforts. In general, decentralized and dynamic swarms introduce uncertainties that single systems do not face as much. While cooperative swarms provide benefits, the coordination and connection volatility aspects have limitations that require ongoing research to fully address.

4.3.11 Open issues related to RQ3

1. Scalability:

   Most studies consider small-scale scenarios lacking rigor at larger scales. An evaluation is needed for optimization techniques for handling industrial scale swarms with thousands of nodes under realistic system dynamics.
2. Security complexity:
   Decentralized access controls and encryption across dynamically changing networks introduce challenges. Moreover, exploration of adaptive security approaches that are resilient to system dynamism needed.
3. Dynamic topology:

Table 4 Comparison between UAV swarms and single or ground MEC for computational offloading

No.	Factor	Single UAV/terrestrial MEC	UAV swarm computational offloading
1	Distributed Decision-Making [110]	Centralized decisions	Decentralized coordination through cooperation
2	Load Balancing (Cooperation) [111]	No cooperation	Task distribution through cooperation & resource sharing
3	Energy Efficiency [67]	Focus on individual energy usage (focuses on single system)	Collective energy optimization leveraging proximity (optimizes collective usage)
4	Privacy and Security [81]	Centralized control & storage (easier to monitor single unit)	Data distributed across swarm raises new threats (decentralized access control needed)
5	QoS [112]	Depends on individual capacity	Improved through cooperative computing resources can aggregate resources spatially
6	Cost Constraints [87]	Infrastructure deployment costs (hardware and operation costs)	Swarm flexibility reduces costs vs infrastructure (economies of scale possible)
7	Communication Constraints [124]	Stable wireless links	Temporary intermittent links impacting decisions (self-organized aerial mesh network)
8	Heterogeneity [60]	Homogeneous resources	Diverse nodes require more complex coordination
9	Applications [103]	Localized processing needs	Applications requiring wide-area sensing, mobile edge services
10	Dynamic Network Topology [119]	Static/predictable topology	Dynamic topology from node mobility raises coordination challenges
11	Limitations	Single point of failure if the node goes offline Restricted coverage area that cannot be expanded Static deployment, cannot follow dynamic users/tasks Load imbalance under varying demands No parallel task processing capability Vulnerable to attacks on the single node	Higher coordination overhead for distributed decision-making Single UAV/node still has limited resources for large individual tasks Dynamic connectivity issues as UAVs move in/out of range rapidly Increased energy costs to maintain numerous wireless links Scalability challenges in controlling a large number of UAVs Requires interoperable hardware/software across UAVs Adds complexity for security, fault tolerance across multiple nodes

Current works oversimplify topology variations that impact offloading. Understanding the effects of rapid connectivity changes on optimization is important.

4. Resource constraints:

   While models optimize objectives, limitations of constrained resources such as bandwidth and energy capacity at scale require investigation. Adaptive algorithms respecting constraints aid feasibility.

4.4 Number of UAVs impacting a swarm on the performance of offloading

This section reports the answer to RQ4 (How does the number of UAVs in a swarm affect the performance of tasks offloading to a UAV swarm?). This question establishes the analytical methods needed to fully address the relationship between the swarm scale and task offloading ability. Understanding scalability differences provides insight into how well methods utilize increasing swarm resources through distributed task allocation. This also indicates method long-term viability as swarms scales up. The offloading performance can be influenced by various factors such as the number of UAVs in the swarm and the algorithm used for task allocation and scheduling. When considering the impact of UAVs in a swarm on the offloading performance, it is important to evaluate the scalability and efficiency of different algorithms. The scalability of an algorithm refers to its ability to handle an increasing number of UAVs in the swarm without a significant decrease in performance [128].

When comparing the scalability of task offloading in UAV swarms, several algorithms have been proposed for task allocation and scheduling in UAV swarm-based offloading scenarios. These algorithms can be categorized into different types based on their architectural approach, such as centralized, distributed, and hybrid-based offloading [156].

4.4.1 Centralized offloading

Centralized offloading algorithms rely on a single central entity (e.g. a base station or a UAV with high computational capabilities) to make offloading decisions for all UAVs in the swarm. As the number of UAVs increases, the computational complexity and communication overhead of the central entity also increase, leading to scalability issues [42]. A central entity, such as a cloud server, is responsible for managing the task offloading decisions for all UAVs in the swarm [157]. The UAV swarm is managed by a centralized controller/server that has an overall view of network resources. The controller uses an optimization algorithm to determine the best UAV to offload each task based on factors such as computational power, energy level, and location. The controller then sends instructions to the individual UAVs about which tasks to execute. UAVs simply follow commands from controllers and do not make independent decisions [124]. If the load on a UAV increases, the controller can reallocate some tasks dynamically to balance resources. The controller also tracks UAV movements and associations to maintain optimal allocation as topology changes. It centrally coordinates all task assignments, scheduling, and distribution of computation results. The centralized approach provides uniform management, but a single controller can become a bottleneck. Failure of the central entity will disrupt the whole system operation until a new controller takes over. Scalability is also a concern because the controller must process data from all UAVs to make optimal assignments [158].

Scalability: In a centralized architecture, where a central entity coordinates and manages the offloading process for the entire UAV swarm, scalability can be affected. As the number of UAVs in the swarm increases, the central entity may face challenges in efficiently allocating tasks and managing the offloading decisions for a large number of UAVs. Centralized architecture may become a bottleneck, leading to scalability limitations [42, 159].

4.4.2 Distributed offloading

Distributed offloading algorithms distribute the decision-making process among multiple UAVs in the swarm. Each UAV makes offloading decisions for itself based on local information and coordination with neighbouring UAVs. Distributed algorithms are more scalable than centralized algorithms because they do not rely on a single point of failure. In distributed offloading, each UAV makes its own offloading decisions based on local information and communication with nearby UAVs [16, 51].

The UAV swarm operates without any centralized controller and makes decisions in a fully distributed manner. UAVs cooperate by sharing information about their capabilities, locations, trajectories, and task loads via localized communication. User devices directly offload tasks to nearby UAVs via D2D communication technology such as WiFi or Bluetooth [160]. Each UAV processes tasks locally based on its available resources. Some tasks may also be forwarded to other UAVs. UAVs negotiate task allocations among themselves via consensus-based algorithms while considering factors such as network topology, mobility patterns, and the affinity of tasks to resources [161]. This allows tasks to be dynamically matched to the most suitable UAVs in real-time based on the collective intelligence of the swarm. Tasks are prioritized and UAVs with more resources accept tasks from resource-constrained UAVs to balance the load. If a UAV fails or moves of range, others reallocate its tasks using distributed coordination to maintain service continuity. The system is self-organized, adaptive, and scalable, and UAVs can autonomously join or leave without any master entity [75]. It provides computational services to users in a distributed manner without relying on centralized controllers which can become bottlenecks.

Scalability: Distributed architectures, where each UAV makes its own offloading decisions based on local information and interactions with neighbouring UAVs, can offer better scalability. As the number of UAVs increases, the distributed nature of the architecture allows for more parallel and independent decision-making. Each UAV can make offloading decisions locally, reducing the dependency on a central entity and enabling scalability [16].

4.4.3 Hybrid offloading

Hybrid offloading algorithms combine centralized and distributed approaches. A central entity is responsible for high-level coordination and resource allocation, whereas individual UAVs make fine-grained offloading decisions based on local information. Hybrid algorithms offer a balance between optimality and scalability. Some offloading decisions are made centrally, while others are made by individual UAVs [71].

The UAV swarm is divided into multiple clusters based on proximity. Each cluster has 3–5 UAVs [162], and within a cluster, the UAVs communicate directly and make task offloading decisions in a distributed manner. They cooperate, share information, and allocate tasks locally. One UAV in each cluster is designated as the cluster head. It has higher computational capabilities. The cluster heads then communicate with each other and a centralized controller (which could also be a UAV) to coordinate tasks between clusters [163]. The user devices offload computational tasks to the swarm of UAVs. Tasks can either be processed locally by UAVs or offloaded further. Cluster member UAVs offload tasks to their cluster head if they do not have sufficient resources or if the task requires more capabilities. The cluster head processes as many tasks as possible. The remaining tasks are forwarded to other cluster heads. Cluster heads negotiate and allocate inter-cluster tasks in a centralized manner based on collective UAV resources and task requirements. UAV movements and failures are also coordinated centrally to maintain optimal clustering. This hybrid approach

Table 5 Comparison of UAV swarm architectures

Architecture	Refs.	Characteristics	Scalability	Limitations
Centralized	[44, 47, 55, 57, 64, 69, 73, 79, 89, 98, 100, 104, 105, 107, 115, 119, 128, 134]	Single controller optimally assigns tasks	Does not scale well as the central controller becomes a bottleneck with increasing UAVs	Single point of failure if the central controller fails Bottleneck as the controller handles all coordination load Not scalable as coordination -complexity increases with swarm size Requires stable high bandwidth backhaul links
Distributed	[15, 16, 21, 36, 40, 45, 60, 62, 65, 67, 77, 81, 87, 99, 103, 106, 110–113, 116–118, 121–124, 126, 129]	UAVs cooperatively assign tasks through local decisions	Scales much better as control is decentralized	Higher coordination overhead to maintain distributed consensus Increased communication latency compared to centralized approach Resources may not be optimally allocated in a fully decentralized manner No global view of network state available
Hybrid	[34, 42, 54, 71, 75, 114, 120, 125, 130–133, 135]	Hierarchical clustered architectures combine centralized intra-cluster and distributed inter-cluster control	Better scalability than centralized by dividing swarm into clusters handled in distributed manner	Increased complexity compared to centralized/distributed alone Single cluster head failure can impact task coordination in its cluster Inter-cluster coordination overhead in addition to intra-cluster Determining optimal number of clusters and cluster sizes is nontrivial

distributes intra-cluster control while centrally coordinating inter-cluster allocations for better scalability and efficiency as the number of tasks and UAVs increase. This approach leverages the benefits of both centralized and distributed control for scalable MEC functionality in dynamic UAV swarms [164].

Scalability: Hybrid architectures, which combine elements of both centralized and distributed approaches, can offer a balance between scalability and coordination. By leveraging the benefits of both architectures, critical or complex tasks can be managed centrally, while less critical tasks can be handled in a distributed manner. This hybrid approach enables scalability by allowing parallel processing of tasks while maintaining centralized control for critical operations [30]. Table 5 compares the scalability of UAV swarm architectures.

Distributed and hybrid architectures are more scalable than centralized architectures for swarm UAV offloading. The mobility and coverage capabilities of UAVs can also contribute to scalability by extending MEC services and reducing the burden on individual UAVs. Additionally, considering the energy efficiency of UAVs can help maintain scalability by ensuring that UAVs have sufficient battery life to support offloading operations.

On the other hand, the type of algorithm used for UAV swarm offloading can have a significant impact on the scalability of the system, particularly in terms of the number of UAVs that can be effectively managed and coordinated. PSO [100] can scale reasonably well as each agent only communicates with topological neighbours. However, as the swarm size increases, maintaining cohesive movement becomes challenging due to the increased variance in the optimal solutions across space. Game theory approaches [106], which utilize concepts such as potential games, achieve faster convergence for best response dynamics with larger populations as equilibrium selection becomes easier statistically. However, modelling complex interactions limits scalability. Distributed machine learning such as Multi-Agent DRL (MADRL) [114] overcomes single-agent training costs and improved with more agents due to increased collection experience. However, stability and shared understanding become issues as agent heterogeneity grows substantially with large swarms. Genetic Algorithms [79] struggle with very large problem spaces as population diversity declines, requiring larger populations that increase complexity. The selection of optimal solutions also becomes more difficult. Consensus algorithms [60] can leverage the repetitive averaging nature to scale linearly with size for simple problems. However, convergence slows and communication costs rise nonlinearly as the number of agents and complexity increase. In general, algorithms that adapt solutions dynamically, such as PSO, DRL, and local-rule nature inspiration, provide better scalability than algorithms that rely on global assessment or infrequent interactions in UAV swarms. However, all of these methods face coordination and noise challenges as group sizes become enormously large.

4.4.4 Open issues related to RQ4

Fault tolerance:

As swarm sizes increase, individual node failures become more common. Existing approaches need to be evaluated for their ability to maintain functionality, redundancy, and graceful degradation as failure rates rise with scale. Distributed recovery mechanisms require further exploration.

1. Scalability:

   While simulations show promise, approaches involving thousand of nodes need testing at extremely large realistic scales involving thousands of nodes. Challenges include managing complexity, constrained resources, and wireless interference given nonlinear increases. Adaptivity to failure/dynamics is also a concern at immense numbers.
2. Coordination constraints:
   As heterogeneity, autonomy, and dynamism grow exponentially with swarm size, so does coordination complexity. Maintaining coherent collaborative behaviour and efficient decision-making under real-time constraints is an open question, especially for massively distributed systems. The adaptive mechanisms that are scalable for industrial deployments require investigation.

Table 6 Limitations in 63 articles on UAV swarm task offloading

No.	Limitation	References	Corresponding open issues	Note
1	UAV deployment is assumed to be static over time	[15, 16, 21, 34, 40, 45, 47, 54, 55, 57, 60, 62, 65, 67, 69, 73, 77, 79, 89, 105, 106, 108–111, 113–115, 117–120, 123–126, 129–135]	Dynamic network topology	Majority of works consider static deployment
2	Consider only one aspect optimized	[44, 47, 65, 75, 87, 98, 100, 107–109, 120, 121, 126]	Multi-objectives solution	Most works only optimize single objective
3	Centralized method may not scale well	[15, 119]	Scalability	Centralized approaches do not consider scalability
4	Does not consider on-demand/real-time computation offloading	[21, 36, 42, 45, 62, 69, 100, 103, 104, 112, 116, 117, 122, 131, 135]	Resource constraints	On-demand offloading not widely studied
5	Connectivity changes as UAVs move	[16, 34, 40, 54, 60, 69, 71, 77, 98, 99, 111–114, 122, 127, 131, 132]	Communication Constrains	Mobility effects not deeply analysed
6	Heterogeneity across devices, traffic workloads, topology conditions not completely captured	[42, 54, 55, 67, 79, 81, 89, 110, 118, 123, 127, 130]	Heterogeneity	The research papers do not discuss how heterogeneity in terminal devices and UAV capabilities would be addressed when those components are sourced from multiple operators or vendors. Specifically, they fail to consider the implications of diversity introduced via third-party suppliers on two important aspects—revenue maintenance and security
7	Does not consider failures	[104, 105, 109, 126, 134]	Fault Tolerance	Only one work mention fault tolerance [42]
8	Data not secure	[100, 107]	Security and privacy	Only 2 articles considering security [42, 104]

4.5 Open issues in UAV swarm offloading

This section reports the answer to RQ5 (What are the key open issues and challenges in task offloading for UAV swarms basis of the current literature?). Identifying gaps and limitations is important for understanding room for improvement and guiding future work. However, simply listing problems provides an incomplete picture. In essence, this question establishes an evidence-based process to define open issues precisely, ensuring the most relevant problems are targeted forward. This optimized the research progress. We provide the literature on UAV swarm computation offloading in a table format along with limitations aimed at identifying open issues in this research area. Summarizing the work in this way allows us to draw conclusions about gaps and opportunities for further study.

A review the literature in Table 6, clearly reveals that the majority of studies did not account for high mobility or changing network topologies. Additionally, only one work [42] mentioned fault tolerance in UAV swarm offloading networks. Consequently, there has been minimal investigation into the interference between UAVs in swarms [121] and fluctuating channel conditions with MEC infrastructure. Security and privacy concerns have only been briefly discussed in a few papers as well, without considering the complex and heterogeneous networking environments involved. Overall, more attention is still needed on these important real-world factors that have not been adequately represented in current models and solutions. Based on the existing literature on UAV swarm computation offloading summarized in the table, several key challenges and open issues can be identified:

4.5.1 Heterogeneity affects revenue and security

Heterogeneity in UAV swarm task offloading refers to the presence of different vendors or operators with varying capabilities, resources, and objectives [45]. This heterogeneity can lead to challenges in interworking between these different entities, including the problem of revenue sharing. This complex issue needs to be addressed to fully realize the potential of UAV swarm computing offloading [165]. One of the main challenges in UAV swarm task offloading is ensuring that devices from different vendors or operators can work together seamlessly. This is because each vendor's devices may have different hardware, software, communication protocols, and coordination mechanisms, making it difficult for them to communicate and work together effectively. Revenue sharing between different operators requires a high level of trust and cooperation. However, in a heterogeneous environment, building trust and establishing fair revenue sharing mechanisms can be challenging. Operators may have concerns about the accuracy and transparency of revenue calculations, leading to disputes and difficulties in reaching mutually beneficial agreements. Moreover, different vendors or operators may have different security measures in place, and integrating their systems may require addressing potential vulnerabilities and ensuring data privacy and integrity [166]. This lack of interoperability between heterogeneous devices can limit the potential of UAV swarm task offloading systems [48, 167]. To overcome this challenge, researchers and developers must find ways to ensure that devices from different vendors can work together seamlessly, enabling efficient and effective cooperation in UAV swarm task offloading systems.

4.5.2 Fault tolerance

Existing works mainly focus on introducing redundancy or backup replication for basic task offloading [168], but achieving fault tolerance through distributed means is challenging at large scales [42]. Fault tolerance for decentralized UAV swarm also requires further study, as resilience to failures has been underexplored topic in the literature. Broader fault-tolerant techniques for general computation offloading scenarios in UAV swarms are lacking. The heterogeneous reliability of various UAV types has also not been well addressed in terms of integrated fault management across diverse swarm resources [146]. Faults can increase due to coupling effects in distributed systems, but dependencies and failure propagation models specific to UAV swarms remain less explored. Few studies have evaluated the fault tolerance overhead or proposed optimization strategies to minimize the performance/energy overheads of redundancy-based approaches [169]. There is a need for adaptive, self-healing methodologies to provide resilience under different fault modes and dynamic swarm behaviours.

4.5.3 Scalability

A large number of drones in swarm and multi-swarm coordination pose several challenges that need to be addressed. These challenges are related to the efficient coordination and control of many drones to ensure smooth and effective operation [55]. Scalability is indeed a major challenge in developing distributed coordination algorithms for large-scale UAV swarms performing collaborative task offloading under dynamic real-world conditions [139]. Most proposed allocation algorithms have high computational costs that increase exponentially or polynomially at the swarm scale [120]. Processing demands grow significantly for large swarms. Real swarms will have heterogeneous UAVs in terms of capabilities. Scaling algorithms to handle diverse drone types adds to this challenge [170]. Additionally, UAV placement, failures, and mobility patterns change rapidly with the large scale of UAVs in a swarm. Consequently, an allocation must adapt to larger, unpredictable swarm behaviours [171].

4.5.4 Resource and communication constraints

Although energy and latency are well-studied objectives in the literature, optimizing communication bandwidth and power for efficient data transfer between UAVs is challenging. Wireless connectivity between mobile UAVs is intermittent [71, 152]. Few works model unpredictable link/channel qualities or multi-hop coordination well [15]. Moreover, task workload demands can be unpredictable, and computation/communication intensive can be challenging [172]. Furthermore, inter-drone interference effects are complex due to near-field flying patterns [173]. Based on the literature reviewed, most existing works that address interference mitigation in UAV swarm networks focus on mitigating uplink interference between terminal devices or drones and UAV swarms or MEC. Techniques such as MIMO (Multi–Input–Multi–Output) [115] and Frequency Division Multiplexing Access (FDMA) [34] are commonly proposed for managing uplink interference during task offloading. However, interference management specifically between UAVs in the swarm itself has not been sufficiently addressed or mentioned in the literature. Accounting for complex interference phenomena between swarming UAVs [71, 121, 133] and time-varying wireless conditions with MEC presents ongoing technical challenges that have not been fully addressed. Moreover, temporary connectivity and topology changes make bandwidth reservation, and congestion control challenging without global knowledge. Additionally, latency gains from optimized task allocation/migration assume ample bandwidth which is not stable in real scenarios [141]. This is often unrealistic under constrained multicasting/broadcasting.

4.5.5 Dynamic network topology

Most work in the literature has focused on computational offloading in UAV swarms, without holistically considering the impacts on other functions such as localization and communication that also need dynamic tuning [57, 174]. There is a limit to understanding how dynamically varying channel conditions, and air turbulence impact [175] task execution. Most works assume static scenarios or simple mobility models that do not reflect real complex dynamics. There are few self-adaptive algorithms that optimize offloading in the face of uncertainties and intermittent disconnections [176]. In dynamic

Table 7 Comparison of different UAV swarm opening issues

Challenge	Heterogeneity affect revenue and security	Fault tolerance	Scalability	Resource & communication constraints	Dynamic topology
Description	Integration with multiple platforms and revenue models Interoperability between heterogeneous systems Secure authentication, access control and privacy between heterogeneous systems offloaded data/tasks	Ability to reallocate tasks if UAVs or MEC fail and ensure continuity of services	Performance well with increasing number of UAVs in swarm	Limited onboard resources and network bandwidth constraints	Adaptation to changing UAV placements, and environmental conditions
Research Gaps	Lack of standardization for platforms/APIs revenue models for shared swarms Legal frameworks Robust multi- operators authentication schemes	Low-latency detection and rapid redistribution for massive failures	Exponential rise in computational/communication overhead	Energy/latency optimizations do not holistically address constraints	Limited testing on large-scale dynamic scenarios over long durations
Evaluation Challenges	Finding a viable business model for UAV swarm computation offloading Ensuring compatibility and seamless integration between different UAV swarm venders Preventing unauthorized access and potential cyber-attacks on UAV swarm systems	Developing mechanisms to handle failures or malfunctions in individual UAVs within the swarm	Ensuring efficient coordination and communication between a growing number of UAVs in the swarm	Optimizing communication bandwidth and latency for efficient data transfer between UAVs	Adapting to changing environmental conditions and unpredictable obstacles in real-time
Represented in literature	Partially (multi-operators used for deployment of UAVs only)	Partially (only a few works consider failures)	Partially (limited to small scale)	Partially (ignore joint optimization)	Partially (assume static topologies or planning path)
Reference	[79, 110]	[42]	[60, 129]	[71, 109, 115]	[100, 103]

environments in UAV swarms, tasks may arrive at any time, requiring immediate offloading decisions and resource allocation. However, the arrival rate and characteristics of tasks can vary, making it challenging to optimize offloading decisions in real-time [177]. Designing dynamic offloading algorithms and protocols that can adapt efficiently to such constantly shifting execution environments is challenging. The issues of around robust task allocation, load balancing, computation migration, and failure handling under highly unpredictable and transient conditions require further research. The development of self-organizing mechanisms allowing UAV swarms to collaborate on the fly is an important open issue [178]. Table 7 compares the open issues discussed in this SLR.

5 Conclusions

In conclusion, this systematic literature review (SLR) paper presents an understanding of UAV swarm offloading. Publications from 2019 to 2023 were analysed to identify key summarizing considerations, classify roles, identify decision-making factors, analyse swarm sizes, and highlight open challenges. Overall limitations such as unpredictable context and heterogeneous swarm environments suggest opportunities for future work incorporating adaptive learning approaches. This review provides insights into the progress and gaps in UAV swarm offloading research to facilitate future work in this promising area. Our SLR provides a useful resource for researchers and practitioners working in the field of UAV swarm task offloading and highlights areas that require further investigation. For future directions, and targeted evaluations of particular architectures and algorithms, comprehensive assessments of clustering-based, blockchain-based, and federated learning-based methodologies are recommended. Additionally, it is advisable to investigate dynamic pricing mechanisms for multi-vendor UAV swarms and standardize the integration of heterogeneous swarms from different providers.

Abbreviations

2D	2 Dimension
6G	Six generation
AI	Artificial intelligence
Aps	Access points
AR	Augmented reality
BS	Base station
CPU	Central process unit
D2D	Device to device
DDPG	Deep deterministic policy gradient
DNN	Distributed neural network
DRL	Deep reinforcement learning
eURLLC	Enhanced ultra-reliable low latency communication
FANETs	Flying ad hoc networks
FDMA	Frequency division multiplexing access
IoDs	Internet of drones
IoTs	Internet of things
IoVs	Internet of vehicles
IPSO	Improved particle swarm optimization
LEO	Low earth orbit
LoS	The line-of-sight
LSTM	Long short-term memory
MADRL	Multi-agent deep reinforcement learning
MDP	Markov decision process
MEC	Mobile edge computing
MIMO	Multi-input-multi-output
ML	Machine learning
PRISMA	Preferred reporting items for systematic reviews and meta-analyses
PSO	Particle swarm optimization

QoS	Quality of service
RL	Reinforcement learning
RQ	Research question
SDN	Software-defined networking
SLR	Systematic literature review
U2X	UAV to everything
UAV	Unmanned Aerial Vehicle
VR	Virtual reality

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Author contributions
Asrar Baktayan developed the research questions and objectives for the review and designed the methodology, including the search strategy, selection criteria, data extraction plan, and quality appraisal approach. Asrar Baktayan and Ammar Zahary discussed major themes and identified implications/gaps based on the analysis. Axel Sikora drafted the different sections of the review paper, coordinated co-authors' inputs and prepared for publication, assigned and oversaw tasks, maintained documentation, and addressed any issues throughout the process. Dominik Welte proofreads the initial manuscript. All authors reviewed and approved the final manuscript.

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