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Applications and Future Perspectives of Swarm Intelligence in Unmanned and Autonomous Systems

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Abstract

This paper examines the potential implications of the principles of swarm intelligence and collective behavior in nature for unmanned systems and autonomous organizational structures. Swarm intelligence is inspired by natural systems in which individual units interact according to simple rules to form a complex and organized whole. These principles can be observed in a wide range of situations, from the synchronized flight of flocks of birds to the harmonized swimming behavior of schools of fish. The study emphasizes that swarm intelligence principles have the potential to create more flexible, resilient and efficient systems with decentralized control mechanisms and autonomous decision-making processes. Furthermore, it is suggested that these approaches can find applications in many fields, from military operations to agricultural and environmental monitoring, from disaster response to urban planning. The study provides a detailed analysis of swarm behavior in nature and discusses how these behaviors can be emulated and optimized in unmanned systems. In this context, the potential impacts of swarm intelligence and collective behavior principles on unmanned systems are evaluated in terms of increasing their adaptability, optimizing energy efficiency and maximizing mission success. It is also argued that these principles can contribute to making unmanned systems more resilient to contingencies and changing environmental conditions. Swarm intelligence principles can be used to provide more effective coordination in unmanned air, land and sea vehicles. In digitalizing sectors, the flexibility of businesses can be increased and resource usage can be optimized by creating decentralized decision-making mechanisms.

Keywords: swarm intelligence, unmanned systems, autonomous organizational structures, principles of collective behavior

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İnsansız ve Otonom Sistemlerde Sürü Zekâsının Uygulamaları ve Gelecek Perspektifleri

Öz

Bu makale, sürü zekâsı ve doğada kolektif davranış ilkelerinin insansız sistemler ve otonom örgütsel yapılar için potansiyel çıkarımlarını incelemektedir. Sürü zekâsı, bireysel birimlerin karmaşık ve organize bir bütün oluşturmak için basit kurallara göre etkileşime girdiği doğal sistemlerden esinlenmiştir. Bu ilkeler, kuş sürülerinin senkronize uçuşundan balık sürülerinin uyumlu yüzme davranışına kadar çok çeşitli durumlarda gözlemlenebilir. Çalışma, sürü zekâsı ilkelerinin, merkezi olmayan kontrol mekanizmaları ve otonom karar alma süreçleri ile daha esnek, dayanıklı ve verimli sistemler yaratma potansiyeline sahip olduğunu vurgulamaktadır. Dahası, bu yaklaşımların askeri operasyonlardan tarımsal ve çevresel izleme, afet müdahalesinden şehir planlamasına kadar birçok alanda uygulama bulabileceği önerilmektedir. Çalışma, doğada sürü davranışının ayrıntılı bir analizini sunmakta ve bu davranışların insansız sistemlerde nasıl taklit edilebileceğini ve optimize edilebileceğini tartışmaktadır. Bu bağlamda, sürü zekâsı ve kolektif davranış prensiplerinin insansız sistemler üzerindeki potansiyel etkileri, uyarlanabilirliklerini artırma, enerji verimliliğini optimize etme ve görev başarısını maksimize etme açısından değerlendirilmektedir. Ayrıca, bu prensiplerin insansız sistemleri beklenmedik durumlara ve değişen çevre koşullarına karşı daha dirençli hale getirmeye katkıda bulunabileceği ileri sürülmektedir. Sürü zekâsı prensiplerini, insansız hava, kara ve deniz araçlarında daha etkili koordinasyon sağlamak için kullanılabilir. Dijitalleşen sektörlerde, merkezi olmayan karar alma mekanizmaları oluşturarak işletmelerin esnekliği artırılabilir ve kaynak kullanımı optimize edilebilir.

Anahtar Kelimeler: sürü zekâsı, insansız sistemler, otonom örgütsel yapılar, kolektif davranış ilkeleri

1. INTRODUCTION

The field of artificial intelligence (AI) and autonomous systems is witnessing rapid growth with significant developments in areas such as robotics, unmanned vehicles and organizational automation (Cognominal et al., 2021). Among the many concepts shaping this evolution is swarm intelligence, a concept inspired by the collective behavior of social organisms such as ants, bees and birds (Rajasekhar et al., 2017). In nature, these organisms exhibit complex collective behaviors that allow them to solve complex problems, adapt to their environment and achieve extraordinary organizational successes without centralised control (Csaszar and Steinberger, 2022).

As rapidly evolving technology and automated systems, unmanned systems and autonomous organizational structures are increasingly integrated into our lives, swarm intelligence and the principles of collective behavior in nature offer significant potential impacts on unmanned systems and autonomous organizational structures (Zhang et al., 2022). Swarm intelligence is based on the idea that simple agents, each following basic rules and responding to local stimuli, can produce complex, adaptive and intelligent behaviors when acting as part of a group (Hasbach and Bennewitz, 2022). This decentralization of decision-making mirrors the way biological swarms function in nature. For example, ant colonies find optimal solutions to food gathering challenges, and flocks of birds exhibit synchronised movements to avoid predators (Berlinger et al., 2021). In both cases, individuals do not have a global view of the problem, but their collective actions result in highly efficient solutions. This decentralized, self-organising approach is of particular interest for artificial systems that must operate in dynamic and unpredictable environments, such as drone swarms, autonomous vehicles and robotics.

Swarm intelligence is a field of study that investigates the principles underlying the collective behaviors seen in nature and how these behaviors can be adapted to technology (Garnier et al., 2007; Brambilla et al., 2013). These behaviors, examples such as the nest building of complex collective ants, the honey foraging behavior of bees and the flight patterns of bird flocks, show how complex tasks can be accomplished through simple individual rules (Abdulsaheb and Kadhim, 2023). Swarm intelligence provides an alternative model for controlling unmanned systems, enabling them to function autonomously and respond to local conditions without the need for centralized coordination (Cai et al., 2023). Inspired by natural systems, swarm-based unmanned systems distribute control over a network of agents, each of which can make decisions based on its local environment. This decentralized control model provides greater adaptability and resilience as the failure of a single agent does not compromise the functionality of the entire system. Swarm-based systems are inherently scalable; they can expand or contract in size without requiring major structural changes, making them ideal for tasks varying in scope and complexity (Bu et al., 2024).

In addition to unmanned systems, swarm intelligence principles have far-reaching implications for the design of autonomous organizational structures. Traditional organizations are often structured hierarchically, with decision-making power concentrated at the top. While this model can be effective in stable environments, it becomes less efficient when flexibility, rapid decision-making and innovation are required. In contrast, the swarm intelligence approach to organization design distributes decision-making across the organization and allows for greater autonomy at the local level (Javaid et al., 2023). By enabling smaller units within an organization to make decisions based on local knowledge, swarm-inspired structures can increase agility and responsiveness. For example, technology companies such as Google and Amazon have adopted decentralized teams that operate with a high degree of autonomy, enabling them to rapidly innovate and respond to market changes in real time (Olivares et al., 2024). The swarm intelligence model encourages collaboration and the formation of continuous feedback loops that can increase organizational resilience in the face of disruptions. In this context, businesses can utilize the same principles that govern biological swarms to create systems that are more dynamic, adaptive and able to evolve in uncertain environments. As technology continues to evolve, the principles of swarm intelligence are likely to play an increasingly important role in the design of both artificial systems and organizational structures, providing new opportunities for innovation and efficiency across multiple sectors. The main research question of this study is "What kind of effects do swarm intelligence and collective behavior principles in nature create on unmanned systems and autonomous organizational structures and how can these effects be best utilized?" By addressing this question, the study aims to make significant contributions to the field in theoretical and practical terms. Theoretically, a new framework is presented for how swarm intelligence principles such as self-organization, decentralized decision-making and adaptability can improve the performance of unmanned and autonomous systems. By synthesizing insights from biology and engineering disciplines, the gap in this field in the literature is filled and a more in-depth perspective is provided. In practice, this research aims to show how collective behavior principles in nature can contribute to more resilient, adaptable and efficient systems. These insights serve as a guide for the design and optimization of unmanned aerial vehicles, robotic systems and other autonomous technologies. These contributions have the potential to contribute to the advancement of next-generation autonomous technologies by addressing the need to provide flexible and scalable solutions in today's complex and dynamic environments. In this respect, the study aims to provide an innovative basis for future applications and research in both technological and organizational fields.

While significant progress has been made in understanding the above dynamics, there remains a gap in the full translation of these principles into practical, scalable solutions for UAVs, robotic systems and other autonomous organizational structures. Existing work focuses on isolated elements of swarm behaviour that have not been comprehensively integrated into broader, real-world applications in autonomous systems (Kolling et al., 2015; Schranz et al., 2021; Araujo et al., 2023). This gap in the literature highlights the need for research that not only examines these behaviours holistically, but also tests their potential impact on system resilience, efficiency and adaptability in complex, dynamic environments. Based on these gaps, this study aims to examine the application of swarm intelligence and collective behaviour observed in biological systems to unmanned aerial vehicles (UAVs), robotic systems and other autonomous structures, and to understand to what extent these principles can be adapted and improved.

2. CONCEPTUAL FRAMEWORK

The rapid advancement of artificial intelligence, robotics and autonomous systems has led to transformative changes in modern technology (Kondam and Yella, 2023). One of the key areas of innovation and research in this field is swarm intelligence, a concept inspired by the collective behavior of social organisms such as ants, bees, birds and fish (Mishra et al., 2013). In nature, these organisms show extraordinary abilities to solve complex problems, organize themselves and adapt to changing environments without centralised control. Organisms living in herds function based on simple local interactions, but the essence of swarm intelligence lies in exhibiting highly coordinated and efficient behavior at the group level (Williams et al., 2017).

The emergence of swarm intelligence has not only expanded the understanding of biological systems, but also opened new horizons in the design of unmanned systems and autonomous organizational structures. Swarm intelligence examines how these natural mechanisms can be utilized to increase efficiency, adaptability and resilience in artificial systems (Tang et al., 2023). The concept of swarm intelligence offers a new paradigm for designing decentralized autonomous systems that can outperform traditional hierarchical structures, especially in environments that require flexibility and dynamic responses to unpredictable challenges. These systems have a wide range of applications, from military drones and robot fleets to disaster response, environmental monitoring, logistics and even business management processes (Schranz et al., 2021).

Autonomous organizations, on the other hand, are self-governing organizations that can function without depending on a central authority and carry out decision-making processes in a distributed structure. These organizations stand out with their flexible, agile and adaptive structures with high ability to adapt to rapidly changing environmental conditions (Tata and Prasad, 2004). Autonomous organizations enable individuals or sub-groups to act in harmony with each other, often minimising the need for centralised control even in complex and uncertain situations (van Vulpen et al., 2024). Such organizations are particularly advantageous in areas that require crisis management, innovation, operational efficiency and high flexibility (Janssen and Van der Voort, 2020). Another example of the collective behaviour principles of social organisms such as bees and ants is wolf packs. When examples of how wolf packs can be adapted to systems that require mission capability, such as unmanned aerial vehicles (UAVs), it is seen that the intelligence of this pack has the ability to make quick decisions, adapt and provide system consistency in dynamic conflict environments. It is considered that these characteristics of wolf packs can increase the effectiveness of UAVs and autonomous organizations in areas such as conflict resolution, team dynamics and crisis management (Akkaya and Yazıcı, 2020).

Autonomous organizations, unlike traditional organizations, have the ability to react quickly to environmental changes without being dependent on a central authority. Due to these characteristics, they have a great potential for the application of the principles of swarm intelligence and collective behaviour. However, there is limited information in the literature on the extent to which autonomous organizations can integrate these principles of collective behaviour and what the implications are for organizational effectiveness. In this study, a comprehensive literature review was conducted to examine the potential impact of the principles of swarm intelligence and collective behaviour in nature on unmanned systems and autonomous organizational structures. Autonomous organizational structures were chosen because they are decentralised, self-organising systems with fast decision-making processes. Accordingly, addressing the applicability of swarm intelligence in autonomous organizational structures aims to fill this gap in the literature.

2.1. Theoretical Foundations of Swarm Intelligence

Swarm intelligence essentially refers to the collective behavior of decentralized, self-organising systems capable of performing complex tasks through simple, localized interactions between agents (Abualigah et al., 2023). The concept was first introduced in 1989 by Gerardo Beni and Jing Wang in the context of cellular robotic systems (Beni and Wang, 1993). Swarm intelligence systems typically consist of a population of simple agents or entities that interact locally with each other and their environment. The agents follow simple rules and although there is no central control determining the behaviour of individual agents, the interactions between such agents, which are local and to a certain degree random, lead to the emergence of ‘intelligent’ global behaviour that is unknown to the individual agents (Bonabeau et al., 1999).

One of the most studied forms of swarm intelligence is ant colony optimisation, introduced by Marco Dorigo in the early 1990s (Dorigo, 2007). Ant colony optimisation is inspired by the foraging behaviour of ants and has been successfully applied to various combinatorial optimisation problems. In nature, ants leave pheromones on the ground to mark the paths between their nests and food sources, and other ants follow these pheromones to efficiently find food. In KKO, artificial ants generate solutions to an optimisation problem and use a similar pheromone update rule to indirectly communicate and find good solutions (Chandra Mohan and Baskaran, 2011).

Another prominent swarm intelligence algorithm is particle swarm optimisation, developed by James Kennedy and Russell Eberhart in 1995 (Kannan and Diwekar, 2024). Particle swarm optimisation was inspired by the social behaviour of flocks of birds or schools of fish. In particle swarm optimisation, a population of candidate solutions, called particles, moves through the search space, influenced by their own best known positions and the best known positions of their neighbours. This process allows the swarm to converge towards optimal solutions (Netjinda et al., 2015).

Principles of collective behavior is another important field that studies complex system dynamics arising from the obedience of individual agents to simple rules. The Boids model developed by Reynolds (1987) is an early example of the study of collective behavior by computer simulations. This model mimics the behavior of flocks of birds as individuals obey three basic rules: separation, alignment and convergence. These rules of thumb are used to understand how individual agents interact with each other and with their environment and provide a powerful framework that can be used in many different applications (Bajec et al., 2007).

The principles of swarm intelligence have various applications in engineering and computer science. In particular, algorithms such as ant colony optimization (ACO) and particle swarm optimization (PSO) have been inspired to solve complex problems (Stützle et al., 2011). ACO aims to find optimal solutions by mimicking the shortest path finding behavior of ants. PSO solves optimization problems by modelling the collective movements of flocks of birds and schools of fish. These algorithms have found successful applications in various fields such as logistics, network design and artificial intelligence (Kennedy and Eberhart, 1997).

Collective behavior and swarm intelligence have an important place in biological research. Studies in this field have focused on understanding the collective decision-making processes of social insects and how individual behavior shapes community dynamics (Sumpter, 2006). For example, the process of selecting a new nest site in bee hives provides in-depth insights into how individual bees share information and make community decisions through the dance language. Such studies are critical for understanding the evolutionary and ecological contexts of complex behaviors in biological systems (Seeley, 2010).

The principles of swarm intelligence and collective behavior have also been applied to human organizations and management sciences. These principles are used in modern management strategies such as distributed leadership, autonomous work groups and flexible organizational structures (Malone, 2004). Considering that human behavior and social dynamics are similar to the principles of collective behavior in nature, theoretical and practical studies in this field offer important contributions to create more efficient and harmonios organizational structures (Wang and Beni, 1989). In this context, swarm intelligence principles develop innovative approaches that emphasise the power of cooperation and collective intelligence in solving complex problems.

2.2. Application of Swarm Intelligence in Unmanned Systems

One of the most prominent examples of swarm intelligence is the foraging behavior of ant colonies. Ants efficiently find and use resources by transferring information to each other through chemical signals called pheromones (Islam et al., 2018). This mechanism is an effective strategy that can be modelled in the coordination and task sharing of unmanned systems such as unmanned aerial vehicles (UAVs). Similarly, schools of fish and flocks of birds move collectively to perform vital tasks such as avoiding predators, finding food, and migrating (Fan et al., 2023). The development of unmanned systems has benefited significantly from theories of swarm intelligence. Autonomous vehicles, drones and robots can operate more efficiently when they are based on decentralised control models rather than hierarchical command structures. Traditional control systems often require constant human intervention or centralised processing, which can lead to bottlenecks, especially in complex or rapidly changing environments (Chen et al., 2023). In contrast, swarm-based systems enable individual agents to make decisions based on local information, providing real-time adaptability and scalability. For example, swarms of drones in military operations can perform reconnaissance or search and rescue missions without requiring direct control over each individual unit. Each drone can operate independently, adjusting its path and behavior based on data from its sensors or communication with other drones. This decentralized approach increases efficiency by reducing the need for centralized control, while also increasing resilience as the failure of one unit does not compromise the entire system. Additionally, these systems are inherently scalable, meaning that the swarm can expand or contract depending on mission requirements without the need for reconfiguration (Mohsan et al., 2023).

The technological realization of swarm intelligence in unmanned systems is also based on multi-agent systems theory, which addresses how autonomous agents within a system interact to achieve a common goal. Multi-agent systems theory extends the basic principles of swarm intelligence by focusing on how agents can co-operate, coordinate and negotiate tasks in a shared environment. In practical terms, multi-agent systems theory provides the computational tools and algorithms necessary to model swarm behavior in artificial systems such as resource allocation, task allocation and communication protocols (Schranz et al., 2021) Swarm intelligence has important implications for the development of unmanned systems, including drones, robotic swarms and autonomous vehicles. The application of swarm principles to these systems enables them to perform complex tasks more efficiently than individual agents or traditional centralized systems. By mimicking the behaviour of biological swarms, unmanned systems can solve problems related to navigation, coordination and task allocation in a decentralized manner (Kappagantula et al., 2023).

An important example of swarm intelligence in unmanned systems is the deployment of swarms of drones for military and surveillance purposes. In these applications, drones operate autonomously and communicate with each other to achieve mission objectives such as area coverage, target identification or search and rescue operations. By distributing control among the swarm, the system can continue to operate even if some drones are disabled, increasing its resilience in hostile or unpredictable environments (Telli et al., 2023). In civilian applications, robotic swarms are used for tasks such as agricultural monitoring, environmental protection and infrastructure inspection. For example, robotic bees or ‘robo bees’ have been developed to aid pollination in areas where natural pollinator populations are declining (Lazic and Schmickl, 2023). Similarly, fleets of autonomous underwater vehicles could be deployed to monitor ocean ecosystems, track pollution levels, or inspect underwater pipelines. In each of these cases, swarm intelligence enables systems to operate autonomously in large and complex environments where centralized control would be inefficient or impractical (Martorell-Torres et al., 2024).

2.3. Autonomous Organizational Structures: Applying Herd Principles

Unmanned systems and autonomous organizational structures are designed and functionalized using the basic principles of swarm intelligence. This offers significant potentials in various fields (Puente-Castro et al., 2022). Unmanned systems collaborate and divide labor among individuals, as in swarm intelligence. For example, unmanned aerial vehicles (UAVs) can work together to track a target or monitor a specific area. Each UAV acts like an individual in a swarm, performing an overall more complex and effective task (Schwarzrock et al., 2018). Swarm intelligence enables organisms in nature to quickly adapt to environmental changes. There is a similar potential for flexibility and adaptation in unmanned systems. For example, a group of robots can act in response to changes in the environment and successfully complete their tasks (Khaldi and Cherif, 2015).

Unmanned systems adopt the autonomy and redundancy capabilities characteristic of swarm intelligence. Each unit can take over the task or compensate for shortcomings in case others become dysfunctional. This increases the resilience of systems (Wang et al., 2023). Swarm intelligence solves complex problems by creating a collective intelligence. A similar principle is used in unmanned systems. For example, a group of autonomous vehicles can work together to perform a search and rescue operation in a specific area or collect data in a complex environment (Wu et al., 2022). Many unmanned systems collect and analyze data from their environment. The principles of swarm intelligence can help to process and evaluate this data more effectively. For example, a group of sensor drones can process the data they collect based on the principles of swarm intelligence and detect changes in the environment (Marek et al., 2024). These potential impacts highlight the important role of swarm intelligence and collective behavior on unmanned systems and autonomous organizational structures. Research and developments in these areas can contribute to the development of more intelligent, flexible and effective unmanned systems in the future.

The application of swarm intelligence principles in the development of unmanned systems and autonomous organizational structures has many advantages. For example, optimizing task allocation and coordination of unmanned systems can increase efficiency and reduce error rates (Zhou et al., 2020). Furthermore, swarm intelligence-based approaches enable the development of more flexible and adaptive systems in dynamic and uncertain environments. This is especially important in mission-critical applications such as search and rescue operations, environmental monitoring, and military applications.

Recent research shows that swarm intelligence principles can be successfully applied in robotic systems. For example, robotic ants perform effectively in finding the shortest path and overcoming obstacles to reach a specific goal (Muhsen et al., 2023). In addition, swarm robots are being developed for use in different sectors such as agriculture, healthcare and logistics. These developments enable unmanned systems to become more intelligent, autonomous and collaborative (Soori et al., 2023).

In addition to unmanned systems, swarm intelligence has a transformative potential in the design of autonomous organizational structures. Traditional organizational models are often based on hierarchical decision-making processes that can limit flexibility and slow responses to change (Saranya and Subhashini, 2023). By applying the principles of swarm intelligence, organizations can create decentralized systems where decision-making authority is distributed among smaller, autonomous units. This approach is particularly advantageous in environments that require rapid innovation and adaptation, such as technology-driven industries and start-ups (Altshuler, 2023). Swarm intelligence theory suggests that decentralized decision-making and self-organization can increase organizational resilience and innovation. For example, rather than relying on a top-down approach, individual teams or departments within an organization are empowered to make decisions based on local conditions and real-time information (Nayak et al., 2023).

One of the key concepts drawn from swarm intelligence is the idea of collective problem solving, where the actions of each agent contribute to the overall solution even without explicit co-ordination. This reflects successful organizational structures in companies such as Google and Spotify, where cross-functional teams work with a high degree of autonomy. These teams work in parallel, experiment with solutions and share their findings in a collaborative environment. By distributing authority and encouraging local innovation, organizations mimic the self-organizing characteristics of natural herds, leading to greater adaptability and efficiency (Moffett et al., 2021). Swarm intelligence offers an alternative approach where decision-making is decentralized and individual units (or teams) within the organization are empowered to make decisions based on local knowledge. Decentralized organizational structures inspired by swarm intelligence emphasise flexibility, collaboration and innovation. Each unit or team works autonomously, but remains aligned with the overall goals of the organization through continuous communication and feedback loops. This model allows for faster decision-making as teams do not need to wait for approval from higher-level management and encourages innovation as teams can experiment and adapt their strategies in real time (Zhou et al., 2020). Companies such as Google, Amazon and Spotify have adopted elements of decentralized organizational structures with small, cross-functional teams working autonomously to solve problems and develop new products (Reiche, 2023). In the context of autonomous systems, swarm intelligence can be applied to the design of self-managing systems that organize themselves according to feedback from the environment. For example, smart grids (autonomous energy distribution networks) are designed to balance supply and demand by allowing individual nodes (such as homes or businesses) to adjust their energy consumption according to local conditions (Powell et al., 2024). These systems are resilient to outages as they do not rely on a central controller and can optimize energy use in real time, just as a swarm of ants adjusts its foraging behavior according to food availability.

2.4. Technological Integration of Swarm Intelligence

The integration of swarm intelligence into both unmanned systems and autonomous organizational structures has been facilitated by recent technological advances in artificial intelligence, machine learning and distributed computing (Puente-Castro et al., 2022). Artificial intelligence algorithms, especially those inspired by natural processes such as genetic algorithms or neural networks, allow the application of swarm behavior in artificial systems. For example, drones can be equipped with AI-powered navigation systems that enable them to adjust their flight paths in response to environmental changes or data from other drones (Caballero-Martin et al., 2024). Similarly, AI can be used to optimize decision-making in decentralized organizational structures, providing teams with real-time data analysis and predictive modelling tools (Kliestik et al., 2023). The use of blockchain technology in organizational structures is another emerging area where swarm intelligence principles can be applied. Blockchain operates on a decentralized network of nodes, each holding a copy of the ledger and independently verifying transactions. This decentralized structure mirrors distributed decision making in swarm intelligence, where each node (or agent) acts independently but contributes to the overall stability and security of the system. Blockchain can be used to facilitate autonomous decision-making in organizations, enabling secure and transparent transactions without the need for centralized oversight (Bhumichai et al., 2024). In addition, advances in robotics and sensor technologies are key to realising the full potential of swarm intelligence in unmanned systems. Robots and drones equipped with advanced sensors and communication systems can work in coordinated swarms, sharing information and making real-time adjustments to their behavior. This capability is crucial in complex environments where traditional control systems can fail due to the need for rapid response or unpredictable changes (Zhou et al., 2020).

3. RESEARCH METHOD

A literature review is a method of analysis based on findings from previous experimental and theoretical studies without collecting primary data. A literature review is ideal for providing conceptual clarity and developing new hypotheses that will move the field forward (Lim et al., 2022). In rapidly developing technological fields such as swarm intelligence and autonomous systems, it is necessary to evaluate the existing information in the literature before conducting more extensive research and to prepare a solid ground for experimental studies to be carried out in the following stages. The literature review method is an effective approach in terms of exploring the field of study, identifying gaps and providing theoretical suggestions on how these gaps can be filled.

In this study, a literature review approach is adopted to examine the potential impact of swarm intelligence and collective behaviour in nature principles on unmanned systems and autonomous organizational structures. The literature review was conducted using various reputable databases including IEEE Xplore, Scopus, Web of Science and Google Scholar to ensure comprehensive coverage of both theoretical and empirical studies on swarm intelligence, collective behaviour in nature and autonomous systems. Keywords such as 'swarm intelligence', 'collective behaviour', 'unmanned systems', 'autonomous systems' and 'biologically inspired robotics' were used in various combinations to capture relevant publications.

Specific inclusion criteria were applied to narrow and organise the search. These criteria included studies published within the last 20 years, with an emphasis on experimental research, theoretical models and review articles examining the application of natural collective behaviours to technological and organizational systems. Advanced search filters, such as limiting results to peer-reviewed journals and selecting relevant subject categories (e.g. robotics, artificial intelligence and organizational behaviour) were also used to ensure the accuracy and relevance of the literature reviewed. The main aim of the study was to gather existing knowledge, build a theoretical framework and present an analysis of previous work in these areas. This systematic approach allows to identify existing research gaps and conceptualise new perspectives and hypotheses. Tools such as Mendeley and Zotero were used to efficiently manage and categorise references, while NVivo was used to code and analyse recurring themes and concepts in the literature, thus providing a structured basis for analysis.

4. FINDINGS

Swarm intelligence has the capacity to create a complex and harmonious structure without a central direction by the combination of collective actions of individuals or subjects. It is seen that herd behaviours seen in nature are a source of inspiration for organizations; it is among the findings that its effects on centralised and decentralised organizational structures have found an increasing application area with technological advances.

Swarm intelligence directs the autonomous behaviour of individuals towards a collective goal and provides flexible and fast adaptability in organizations (Puente-Castro et al., 2022). For example, in processes such as scanning a specific area with the coordinated movement of a series of drones, minimal interaction between individuals provides maximum efficiency and can quickly adapt to environmental changes (Caballero-Martin et al., 2024). Especially in distributed organizational structures, it is observed that it accelerates decision-making processes and facilitates individuals' perception, analysis and application of environmental data (Kliestik et al., 2023). In such autonomous systems, it is among the findings of the literature that swarm intelligence provides a significant increase in decision-making mechanisms and adaptation capacity of organizations.

Table 1 below shows the differences between centralized and distributed organizational structures.

Table 1. Differences between centralized and distributed organizational structures

Feature	Central structure	Distributed structure
Decision making process	From a single center	Among individuals
Flexibility	Low	High
Adaptation Speed	Slow	Fast
Efficiency	Medium	High
Security	Single point failure risk	Distributed secure

Source: Author's own design

Decentralised organizational structures become more dynamic, flexible and adaptive by applying swarm intelligence principles and technologies. In centralised systems, the fact that the decision-making process depends on a single centre increases the risk of late reaction to environmental changes. However, thanks to the capacity of individuals or groups to act independently in decentralised structures, these structures can respond quickly and efficiently to environmental changes. For example, the distributed network structure of blockchain technology provides a transparent and reliable transaction environment by eliminating the need for centralised decision-making mechanisms (Bhumichai et al., 2024). This accelerates the functionality of swarm intelligence and decision-making processes in decentralised organizational structures.

Advances in robotics and sensor technologies allow swarm intelligence to be applied more effectively in complex and unpredictable environments. For example, robots or drones that communicate with each other respond quickly to environmental changes using the principle of swarm intelligence. This structure provides an advantage in situations where individual decision-making is difficult, especially in dangerous or dynamic environments (Zhou et al., 2020). Thus, drones or robots operating with decentralised structures can be enabled to perform individual tasks by quickly adapting to environmental conditions.

Blockchain brings the principles of swarm intelligence to corporate structures with its distributed structure and autonomous processing capacity. The ability of each node to act independently provides a secure data processing infrastructure without depending on a central authority. This maximises the potential of swarm intelligence by increasing both the security and processing speed of decentralised organizational structures. Through these structures, organizations can create a working environment based on transparency and trust between individuals or units (Bhumichai et al., 2024).

Table 2 below provides a summary of the current and practical application ranges of swarm intelligence principles.

Table 2. Current and practical application areas of swarm intelligence principles

Swarm intelligence principle	Application area	Effect
Self-organization	UAVs, robotic system	Operational efficiency
Decentralized decision making	Blockchain technology	Fast decision making, secure data sharing
Easy access to environmental data	Search and rescue activities	Fast and safe intervention

Source: Author's own design

It is observed that swarm intelligence principles are widely applied in autonomous organizational structures and decentralised systems, accelerating decision-making processes, adapting quickly to environmental changes and providing a secure data sharing environment. These findings demonstrate how swarm intelligence can be used to improve organizational efficiency in centralised and decentralised organizations.

5. DISCUSSION

Swarm intelligence is a concept that emerged from the study of the principles of collective behavior in nature and has a wide range of literature from biology and natural sciences to engineering and computer science. In particular, collective behaviors in nature, such as swarms of ants, bees and birds, constitute the centre of swarm intelligence. In recent years, these behavioral principles have been applied to unmanned systems and autonomous structures. However, the question of the adaptation of this theoretical framework to unmanned systems and the extent to which these systems can function similarly to swarm behaviors in nature is addressed with different approaches in the literature.

The concept of swarm intelligence in nature is defined by individuals acting within the framework of simple rules and exhibiting complex and organized behaviors without the need for centralized management. For example, the boids algorithm proposed by Reynolds (1987) is a model developed to simulate the behavior of flocks of birds and shows that individuals act in harmony with each other only through local interactions. This model constitutes an important reference point for the coordination and autonomous behavior of unmanned systems. Systems such as unmanned aerial vehicles (drones) or autonomous robots act in accordance with the principles of swarm intelligence by adopting these local interaction principles (Da Silva et al., 2008).

However, Reynolds' model is more focused on animal behavior in nature and the applicability of these principles to unmanned systems is limited. Here, it should be taken into account that more advanced decision-making mechanisms are needed for unmanned systems to fulfil more complex tasks. Other studies in the literature propose more advanced algorithms to overcome this deficiency. For example, the ant colony algorithm developed by Dorigo et al. (2006) aims to improve the ability of autonomous systems to solve complex optimization problems by mimicking the pheromone trails used by ants in the foraging process. This algorithm shows that unmanned systems can be particularly effective in processes such as route planning and workload distribution.

The adaptation of theoretical models of swarm intelligence to unmanned systems is addressed in the literature with two main approaches: the biomimetic approach and the artificial intelligence-based approach. While the biomimetic approach aims to replicate the collective behavior of living organisms in nature, the artificial intelligence-based approach aims to provide a more advanced model by combining these natural behaviors with human creativity and algorithmic processes. In the biomimetic approach, the decentralized decision-making processes of herds in nature are at the forefront. This approach suggests that unmanned systems can provide advantages in terms of energy efficiency, adaptability and fault tolerance (Passino, 2002). For example, the division of labour and role distribution in bee colonies is used as a model for autonomous robot systems. However, there are limitations on the applicability of biomimetic approaches in unmanned systems. While living things in nature have gone through an evolutionary process of millions of years to adapt to their environment, the capacity of unmanned systems to provide this level of flexibility and adaptability is limited (Yazıcı and Kınay, 2021). On the other hand, the AI-based approach is to simulate more complex swarm behaviors using technologies such as machine learning and data analysis to overcome these limitations. In particular, thanks to deep learning algorithms and big data analysis, unmanned systems have the ability to learn from environmental data and thus become more flexible and adaptable (Rashid and Kausik, 2024).

The potential impact of swarm intelligence principles on unmanned systems has been addressed with various applications in different disciplines. Especially in the military field, swarms of unmanned aerial vehicles are used in reconnaissance and attack missions. For example, in a study by Wang et al. (2024), it was stated that unmanned aerial vehicles can act in a coordinated manner without centralized control with swarm intelligence principles. This supports fast and dynamic decision-making processes in military operations. In contrast, the applicability of swarm intelligence in areas such as agriculture and industry remains more limited. The use of agricultural drones in processes such as monitoring crops and optimizing irrigation systems relies on a limited capacity for autonomous movement (Spanaki et al., 2022). However, the literature on the impact of swarm intelligence on autonomous organizational structures is limited. Studies on the adaptation of swarm intelligence principles to organizational structure and management processes have been mostly limited to simulations and theoretical models. For example, Zorzi et al. (2015) investigated the potential impact of swarm intelligence on distributed leadership and flexible collaboration processes, but provided limited data on how these theoretical models can be translated into practical applications.

Swarm intelligence helps unmanned aerial vehicles and unmanned ground vehicles provide efficient coordination in disaster management, enabling them to share information and select routes in large areas without central control. It has been observed that unmanned aerial vehicles and unmanned ground vehicles facilitate rapid information flow in search and rescue activities, especially in disasters such as earthquakes and fires, facilitating access to the region by emergency teams (Wang et al., 2024). In such natural disaster scenarios, the ability of vehicles to act in harmony with each other with swarm intelligence principles contributes to search and rescue processes by accelerating access to important points (Passino, 2002; Da Silva et al., 2008).

Swarm intelligence also offers energy efficiency and process optimization in a wide range of applications from industrial robotic systems to agriculture and logistics sectors. In production and assembly lines, autonomous robots performing tasks collaboratively provide a continuous workflow without the need for human intervention, thus saving labor and providing a fast production environment. In addition, applications such as the use of drones that provide energy efficiency in agricultural areas and route optimization in logistics create cost advantages and support sustainable operations. The distributed decision-making and flexible leadership principles of swarm intelligence allow autonomous work groups in organizations to work efficiently on their own initiative (Wang et al., 2024).

6. CONCLUSION

This study examines the basic principles of swarm intelligence in nature and seeks to understand the potential impact of these principles on unmanned systems and autonomous organizational structures. Swarm intelligence is a form of collective behavior observed especially in biological systems and is characterized by features such as cooperation, adaptation and coordination. These characteristics in natural systems seem to be a source of inspiration for the development of unmanned systems and autonomous structures. One of the most important results emphasized in the research is that more efficient and flexible systems can be designed by integrating the distributed decision-making mechanisms and autonomy principles of swarm intelligence into the functioning of autonomous systems. Swarm intelligence, which has a decentralized structure, offers a model that allows each individual to act with environmental feedback. The use of this model in unmanned systems such as unmanned aerial vehicles (UAVs), autonomous land and naval vehicles provides the capacity for rapid adaptation and more flexible response to environmental changes.

Another important component of swarm intelligence in nature is that simple interactions of individuals with each other lead to large-scale complex behavior. This principle of collective behavior offers new opportunities to improve the collective coordination and cooperation of unmanned systems. For example, in a swarm, each individual making decisions using only local information leads to high efficiency throughout the system. This principle could lead to the development of autonomous robots and machines that act in concert with each other without the need for human intervention. Another important finding is that the adaptive capacity of swarm intelligence contributes to making unmanned systems more resilient to changing environmental conditions. In particular, the ability of autonomous systems to react quickly to environmental factors increases thanks to swarm intelligence-based algorithms. This adaptability is especially important for disaster management, search and rescue operations and unmanned operations in harsh geographical conditions. The potential impacts of swarm intelligence on autonomous organizational structures are also presented in the study. Autonomous structures offer a more horizontal and autonomous organizational model instead of traditional hierarchical structures. Swarm intelligence principles create a model that allows such structures to be managed more effectively. In particular, accelerating decision-making processes and strengthening coordination can increase productivity in autonomous organizations. The rapid information sharing and reaction capabilities observed in herd systems in nature can contribute to organizational agility by increasing the speed of innovation and adaptation in organizational processes. The operation of autonomous structures with such a model offers a strategic opportunity for companies that want to gain competitive advantage, especially in a digitalised world.

The findings obtained in this study show that the decentralized, environmental feedback-based and adaptive structure of swarm intelligence can enable flexible and efficient operation in autonomous systems. In particular, the more effective coordination and rapid adaptation capacities of unmanned aerial, land and marine vehicles in areas such as disaster management emphasize the importance of swarm intelligence algorithms. In addition, swarm intelligence principles for autonomous organizational structures make a significant contribution to strengthening decision-making processes and coordination by accelerating the operation of a horizontal organization model instead of traditional hierarchical structures. The study fills the existing theoretical gap in the integration of swarm intelligence into autonomous systems and provides strategic implications for how these principles can be evaluated in practical applications.

7. LIMITATIONS

The results of this study address the potential impact of swarm intelligence on unmanned systems and autonomous organizational structures, but face several limitations. The first limitation of the study is that the theoretical basis of the relationship between swarm intelligence and unmanned systems is still evolving. The concept of swarm intelligence has been derived from various disciplines such as biology, computer science, and engineering, and the different approaches offered by each discipline create difficulties in terms of theoretical integrity. Therefore, the theoretical framework used in our study is limited to concepts and principles directly taken from one discipline. In particular, the focus has been on the biological origins of swarm intelligence and its applications in nature, but these principles may not be sufficient to explain the effects of unmanned systems and autonomous structures. More research is needed on how swarm intelligence bridges these two fields. Technological limitations are another important factor affecting the applicability of swarm intelligence and unmanned systems. The fact that swarm intelligence algorithms are based on advanced data processing and sensor technologies creates limitations due to the fact that these technologies are still in the development stage. In particular, more powerful hardware and software systems are needed for autonomous systems to process environmental data in real time and make quick decisions based on this data. Since current technologies do not fully meet these requirements, technological infrastructures need to be further developed in order for swarm intelligence to be implemented to its full potential.

8. IMPLICATIONS

8.1. Theoretical Implications

This study emphasises the contributions to the theory of distributed decision making and discusses the relevance of the basic principles underlying this theory and its place in the literature. Distributed decision-making theory examines situations where individuals or system elements can make collective decisions using their local knowledge without relying on a centralised authority. This theory is in line with the principles of swarm intelligence, since swarm intelligence shows that independent individual interactions observed in nature can lead to complex and harmonious outcomes on the whole system (Caballero-Martin et al., 2024).

Our study not only shows how distributed decision-making theory can lead to faster and more flexible decision-making compared to classical centralised decision-making processes, but also extends the literature. For example, applications of swarm intelligence in autonomous systems reveal that simple information sharing and interactions between individuals can effectively drive complex organisational processes (Puente-Castro et al., 2022). This highlights the capacity of distributed systems to adapt to environmental changes and the potential to reduce the need for a central authority in autonomous organisations.

Furthermore, our study reinforces these themes in the literature by examining the capacity of distributed information sharing technologies, such as blockchain, to support decentralised decision-making processes in a trustworthy and transparent manner (Bhumichai et al., 2024). In this context, new insights are provided on the impact of distributed decision-making theory on information technologies and communication networks, and this study opens up a broad research area for researchers, especially in terms of communication theories in complex systems. In conclusion, our study contributes to a deeper understanding of the potential impact of distributed decision-making theory on autonomous systems and communication networks, demonstrating its role in the creation of more dynamic and rapidly adaptive systems.

8.2. Practical Implications

Swarm intelligence principles can be applied especially in systems such as unmanned aerial vehicles, unmanned land vehicles and unmanned sea vehicles. These systems can perform more coordinated and effective operations by acting similarly to the functioning of swarms in nature. Swarm intelligence principles offer significant opportunities to increase flexibility and adaptation in organizations. Especially in the digitalizing and rapidly changing business world, it is possible for organizations to establish decentralized, autonomous decision-making mechanisms by adopting a structure based on swarm intelligence. Swarm intelligence models have great potential in industries such as energy management, logistics and urban planning. Especially in smart city projects, the use of swarm intelligence principles for more efficient management of energy and resources can optimize energy consumption. For example, in regions with high energy demand, swarm intelligence models can enable the development of autonomous systems that can make decisions on how to use resources most efficiently. These systems can help use energy more sustainably and efficiently by integrating with distributed energy management systems that work with real-time data. The defense industry is one of the areas where unmanned systems are most intensively used. The use of swarm intelligence principles in military operations can increase security and operational effectiveness. For example, unmanned aerial and ground vehicles working in coordination to neutralize enemy elements can increase the success of operations. At the same time, such systems can contribute to the development of more flexible and rapid decision-making mechanisms in defense strategies. Swarm intelligence offers effective solutions in search and rescue operations. Especially in natural disasters, unmanned systems moving in a swarm formation can accelerate search and rescue operations. These systems can help detect missing people more quickly by acting in harmony with each other in disaster areas without the need for human intervention. In addition, these systems can conduct safer operations in difficult geographical conditions and risky areas.

9. RECOMMENDATIONS FOR FUTURE RESEARCH

The first suggestion for future research is to examine interdisciplinary studies in more depth and combine these areas. In the future, it should focus on deepening the integration of swarm intelligence and artificial intelligence. By incorporating the learning and adaptation capabilities of artificial intelligence into swarm intelligence algorithms, more dynamic and unmanned systems that can quickly adapt to environmental changes can be developed. In the future, swarm intelligence will be tested in real-world scenarios and its wider application will be possible. In this context, it is suggested to initiate pilot projects for swarm intelligence and unmanned systems. For example, pilot projects for real-world applications of swarm intelligence and artificial intelligence integration can be initiated; these projects can be implemented in areas such as autonomous vehicles, intelligent logistics systems or disaster management. Within the scope of experimental approaches, the efficiency, speed adaptation and resilience of swarm intelligence-based systems to environmental changes can be tested. In addition, virtual simulations can be used to examine leadership and collaboration dynamics within autonomous organizational structures. These simulations can deeply investigate the role of swarm intelligence in motivation, decision-making and task distribution by analyzing the interactions between employees and systems. Studies on education and human resources development may include creating various skill development programs and training modules to understand how students and employees can work more effectively with swarm intelligence and unmanned systems. These projects will provide an important roadmap for the sustainable and responsible integration of technology. The ethical and social dimensions of the application of swarm intelligence in unmanned systems and autonomous organizational structures should be an important part of future research. In particular, research on the impact of autonomous systems on humans, security concerns, and social acceptance of these technologies will contribute to the responsible development of technology. Swarm intelligence has great potential not only in unmanned systems but also for organizational structures. How swarm intelligence can be used in autonomous organizational structures should be examined in more detail. Especially in the digitalizing business world, how swarm intelligence models can be used to create more flexible, adaptable, and autonomous organizational structures should be investigated. Future research should also examine how concepts such as leadership, motivation, and collaboration can be redefined in such organizational structures.

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