Drone Swarming – Unlocking the Potential of Human Swarm Teams

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SUMMARY

Drone swarms represent a paradigm shift in human autonomy teaming while also bringing unprecedented advantages to civilian and military applications. While enabled by high levels of autonomy, human operators will continue to play a vital role, interacting with the swarm as a single entity, overseeing the mission and making key decisions. This paper discusses the human factors considerations associated with human swarm teams and introduces a bespoke human swarm teaming philosophy for a future drone swarming concept. Integrating autonomy and human information processing models, this concept of control allows the dynamic sharing of tasks between the autonomous swarm and the human operator while optimising key human factors considerations like situational awareness, workload, attention and fatigue. The first principles and designs of a novel human machine interface developed to implement this human swarm teaming philosophy while accounting for the real-world challenges associated with imperfect data transmission and beyond line-of-sight communications are also presented and discussed.

KEYWORDS

Drone Swarming, Autonomy, Teaming

Introduction

Drone swarms are systems of multiple drones where each individual drone has the ability to sense its current state, perceive and respond to its environment and function autonomously to achieve a shared, collective goal. A swarm is considered a single entity, with human operators interacting with it as a whole, instead of controlling individual drones. As such, drone swarming has seen increased interest owing to its scalability, adaptability, high resilience and the importance of affordable mass. While smaller drone and multi-agent systems have revolutionised modern warfare in theatres like Ukraine, the value of drone swarms is yet to be fully realised and can only be unleashed by utilising appropriate levels of autonomy and human swarm teaming to deliver the desired effects (Kolling et al., 2016; Verbruggen, 2019; Connor et al., 2020; Chung & Daniel, 2023; Lyons et al., 2025).

Human Swarm Interaction

Human Swarm Interaction (HSI) refers to the mechanisms underlying interactions between human operators and swarms. Despite the necessarily high levels of autonomy in a swarm, human operators will continue to play a pivotal role, commanding the swarm, setting goals, serving as a moral agent and ensuring mission safety and success. Human strengths like intuition, experience, problem solving, decision making and moral and ethical agency are critical to the effective operation of swarms. (Walker et al., 2013; Kolling et al., 2016; Verbruggen, 2019; Bjurling et al., 2020; Lyons et al., 2025). These strengths, combined with the varied abilities of a swarm, are central to enabling HSI through effective human swarm teaming. However, research in this area is still in its infancy.

Historically, the role of the operator and the model of human control changed in the transition from crewed to uncrewed aircraft, and from single uncrewed aircraft to multi-drone, non-swarming uncrewed systems. It is recognised that swarming may transform the role of the operator and underlying human control models in a similar way. In non-swarming multi-drone systems, the human operator may need to sequentially pay attention to each drone. Thus, operator workload and effort are linearly related to the number of drones within the system – as more drones are added, more operators may be required. The number of drones a human operator can reasonably and directly control is referred to as the fan-out (Olsen & Wood, 2004). The fan-out number and the availability of human operators impose limitations on tolerable mental workload, costs and scalability of multi-drone systems.

Swarms overcome these problems by altering the control ratio, whereby the human operator treats the swarm as a single entity, allowing him/her to oversee multiple drones simultaneously with (theoretically) no significant impact on workload. This is facilitated by the autonomy integral to the swarm, which enables behaviours like coordination, deconfliction and flocking, allowing the human operator to focus on the goal of the swarm instead of on its individual constituents. As a result, swarming calls for a paradigm shift in control ratios, whereby a single human operator may be able to control multiple autonomous drones simultaneously as one single entity. This, in turn may have a series of implications on key human factors considerations like workload, situational awareness (SA) and fatigue (Coppin & Legras, 2012; Kolling et al., 2016; Källbäcker & Bjurling, 2023).

A study by Bjurling et al. (2020) highlighted the following levels at which human swarm teaming may occur:

- Level 1 Swarm: The operator focuses on managing and supervising the entire swarm by providing navigational data, enabling behaviours and monitoring system information.
- Level 2 Subswarm: Subswarms may emerge when swarm assets are self-organised (or commanded by the human) to spread out across a larger area. Subswarms may also emerge when heterogenous swarm assets are allocated tasks tailored to their specific payloads.
- Level 3 Individual Assets: Interaction at this level is similar to current multi-drone system operations but may be infrequent. However, here, the operator will inherit information from other swarm levels and may need to be aware of what the whole swarm is doing.
- Level 4 Sensors and Equipment: This level involves interaction with payload such as sensors, cameras, etc available to the swarm and to individual drones.

The researchers suggested that in real-world settings, human operators are likely to switch between different levels of the swarm interaction model. However, this is likely to depend on swarm size, its autonomous abilities, the operational use case and the human swarm teaming philosophy. There may be cases where the level of data or the number of assets preclude operation at levels 3 and 4. In other cases, like managing a homogenous swarm, the operator may only need to operate at level 1.

Human operators overseeing swarms will occupy supervisory roles, with potentially long periods of inactivity punctuated by short, intense periods characterised by the need for high levels of SA, workload and decision making. Instead of focusing on individual tasks and actions, human operators will monitor more macro-level goals, with the autonomy-enabled swarms coordinating tasks and actions. With the scale of swarms, it is critical that the mechanisms through which operators interact with the swarm are designed appropriately (Pendleton & Goodrich, 2013).

Swarming brings several human factors challenges associated with supervising complex systems. Research shows that human supervisors of existing autonomous systems face problems associated with inconsistent mental workload, lowered vigilance, boredom, stress, fatigue, complacency, lowered SA and skill degradation (Parasuraman et al., 2000; Coppin & Legras, 2012, Verbruggen, 2019). Swarm operators will have to deal with the cognitive complexity of accomplishing goals with swarms, understanding, visualising, and predicting swarm states and ensuring effective swarm management. Given the high number of assets, their emergent behaviours and the opacity of such behaviours, the degree of operator intervention and its impact on mission performance can be difficult to ascertain. Effective human swarm teaming will need to consider the size of the swarm, diversity of assets, the flow of information, the level of autonomous abilities, task and system design, control loops and communication (Ekelhof & Persi Paoli, 2020; Soorati et al., 2021; Källbäcker & Bjurling, 2023). In modern command and control, establishing a shared tactical picture and SA between decision makers and on-field actors is done through constant information flow and is key to mission success (Alberts & Hayes, 2006; Stanton et al., 2008). However, a distributed swarm may be commanded by a human operator who is further away from the swarm's area of responsibility (AOR). Here, effective human swarm teaming requires the operator (and other actors in theatre) to have sufficient SA of the swarm's current state and an ability to estimate its state over a period of time (Walker et al., 2013; Kolling et al., 2016; Verbruggen, 2019). However, this may not always be possible owing to real-world considerations like the lack of beyond line-of-sight communications, use of electronic warfare, jamming, stealth and low observability demands, limits on data transmission and the lack of data modules on expendable assets. HSI philosophies, interfaces and systems must take these into account and be designed around the operator to enable effective human swarm teaming (Verbruggen, 2019; Kim et al., 2020; Lyons et al., 2025).

Trust

According to Mayer et al. (1995), trust is defined as one's willingness to be vulnerable to another entity. In the case of swarms, trust refers to the human operator's willingness to believe that the swarm will perform as required. Trust is already a known human factors challenge in the operation of highly autonomous systems and is also very likely to impact human swarm teaming.

Operator trust in both human and autonomous teammates is fluid and not constant. Trust may be lost when the swarm is unreliable or performs unexpected behaviours. It may be built through familiarity with the system and consistent, reliable performance. Trust in autonomous swarms can be influenced by a plethora of factors including individual operator traits, organisational processes, system transparency and explainability, system design and training. In order to trust the system, operators must be able to understand why the autonomy is working in a particular way and what limitations it may have. Trust also needs to be carefully calibrated - under certain conditions, operators may be inclined to over-trust or under-trust the system, resulting in adverse impacts on mission performance (Verbruggen, 2019; Källbäcker & Bjurling, 2023; Lyons et al., 2025).

System-Wide-Trust (SWT) refers to an individual's tendency to generalise their trust for a system based on interactions with its individual components. Component-Specific-Trust (CST) refers to an individual's trust for components within a system based on interactions with those individual components alone (Keller & Rice, 2009). Studies have indicated that when one system component performs poorly, the lowered CST for that component translates and bleeds over into lower overall trust (SWT) for the system as a whole. This indicates that SWT may be the primary trust mechanism in human swarm teams and that failure of individual components, even those not critical to mission success, may adversely impact operator trust in the swarm (Rice & Geels, 2010; Geels-Blair et al., 2013; Rice et al., 2016; Capiola et al., 2022; Walliser et al., 2023; Lyons et al., 2025).

Research shows that human operators are more likely to perceive a system positively if they can share workload with the swarm, taking and giving back tasks as required rather than being confined to a fixed autonomy state. Systems providing a balance between autonomy and human control have been found to elicit greater trust than fully autonomous or manual systems. In fact, giving operators the option to switch between levels of autonomy has shown to help balance trust, performance, and workload (Ruff et al., 2002; Rovira et al., 2007; Coppin & Legras, 2012; Nam et al., 2020).

Human Swarm Teaming and a Swarming Concept of Control

An effective Concept of Control (CoC) is key to unleashing human swarm teaming. It outlines the way human operators and the swarming autonomy could work together to achieve collective goals and informs the design and implementation of the swarming Human Machine Interface (HMI).

Autonomy (like automation) is not discrete or binary but can vary across a spectrum or continuum of levels (Parasuraman et al., 2000). An automation scale, initially proposed by Sheridan and Verplank (1978), has been used and modified extensively to evaluate different levels of automation modes for supervisory control in robotics platforms and HSI systems (Parasuraman et al., 2000; Coppin & Legras, 2012; Walker et al., 2013; Kolling et al., 2016). The 10-point scale has differing Levels of Automation (LOA) characterising the degree of human control within a system, ranging from full human control (level 1) to full autonomous control (level 10). Levels 2 to 4 answer the question “who decides?”, whereas levels 5 to 9 focus on how the decision is implemented (Parasuraman et al., 2000; Coppin & Legras, 2012).

Over the years, the model was expanded to include the four stages of information processing – information acquisition, information analysis, decision selection and action implementation. A given autonomous system is scored using the LOA scale for each stage of information processing, generating the system’s autonomy profile (Sheridan & Verplank, 1978; Endsley et al., 1997; Parasuraman et al., 2000). Proponents of this model argue that the autonomy level for a given function should not be fixed but instead must vary and be adaptive, depending on the demands of the situation and the state of the swarm. This highlights the importance of using a balanced approach to human swarm teaming, with different situations requiring different levels of autonomy and human intervention for the same function or phase of mission (Parasuraman et al., 2000; Ruff et al., 2002; Rovira et al., 2007; Coppin & Legras, 2012; Walker et al., 2013; Nam et al., 2020).

Boyd’s (1996) work on disruption of enemy decision-making processes, called the OODA loop, consisted of four key functions associated with information processing:

- Observe (O): Sensing, collecting and monitoring data.
- Orient (O): Data analysis and trend prediction, resulting in a series of options.
- Decide (D): Decision making based on options provided.
- Act (A): Implementation of the chosen option.

Compared to the four-stage model proposed by Parasuraman et al. (2000), the OODA loop added the concepts of feedback and implicit control, both relevant to drone swarms. Feedback at the decision point indicates that decisions don’t necessarily translate into actions but can be used to develop new hypotheses and requests for observations. Implicit control and guidance run in the background, representing a level of human supervision and management (Proud et al., 2003).

Coppin and Legras’ (2012) autonomy spectrum centred the design process on the human operator, allowing the dynamic sharing of responsibilities between the operator and the swarm by enabling multiple control modes and LOAs for a given task. The operator was able to choose a particular level of autonomy for a given task, depending on their workload, the task at hand, situational demands, etc. The BAE Systems (2020) concept of control taxonomy proposed a set of five autonomy behaviours that represented levels of human-autonomy task sharing. Each behaviour outlined how tasking and decision making was shared between the operator and the autonomy.

Table 1: BAE Systems (2020) human autonomy teaming behaviours

Level of Human Control	Autonomy Behaviour	Description of Behaviour
Human Control Required	Passive	The system provides information to the human operator
Human Control Preferred	Self-Doubting	The system supports and seeks human involvement in decision making
Human Understanding Required	Explanatory	The system makes the decision, but explains its reasoning to the human operator
Human Awareness Required	Informative	The system makes the decisions and informs the human operator that the decision has been made, but doesn't provide any reasoning
No Human Involvement Required	Reclusive	The system makes the decision, but doesn't communicate anything to the human operator

For this work, the bespoke human swarm teaming concept developed by the author integrates Boyd's (1996) OODA loop with the BAE Systems' (2020) human autonomy teaming behaviours model (see Table 1). This allows for the design of an adaptive autonomy system focused on dynamic task and workload sharing between the human operator and the swarm. The use of OODA outlines the different functions a particular task or mission may have and the different autonomy modes each function could be conducted in. This, in turn, provides a macro-level view of how such an adaptive autonomy system may function to enable the human swarm team's pursuit of a shared goal.

The proposed CoC can be best understood using the example of a swarm tasked with travelling to an AOR, identifying objects of interest and prioritising them as targets. Three hypothetical criteria determine the autonomy level for a given function – whether the system's data confidence is greater than 70% (a notional datapoint), whether the AOR is classed as urban or rural and whether the prevailing rules of engagement (ROE) are normal or heightened. Given this hypothetical mission and its parameters, the human swarm teaming may be based on the following design principles and assumptions:

- Collecting the data *(Observe)* is a highly autonomous activity with no human involvement. The system operates in "reclusive" mode, with no information provided to the operator.
- When an object of interest is identified, classification *(Orient)* may take place across multiple autonomy modes depending on confidence level and the type of AOR:
    - When confidence level is higher than 70% and the AOR is rural, the system operates in "informative" mode, classifying the object as one of interest and informing the operator when classification is complete.
    - Should either criterion not be met, human involvement is required to assess the data and confirm if the object is one of interest. Thus, for the same function, the system now operates in "self-doubting" mode with increased human involvement.
- Once classified, the system uses tactical data, geographical metadata, ROE and pattern of life information to prioritise the objects of interest as targets. The autonomy modes for this process *(Decide)* are as follows:
    - When confidence level is greater than 70%, the AOR is rural and ROE are normal, the system completes prioritisation and then provides the operator with an explanation of its logic. Here, the swarm operates in "explanatory" mode.
    - Should any one of these criteria not be met (confidence level less than 70%, AOR is urban or ROE are heightened), the system drops to the lowest autonomy level of

"passive", where the human operator has complete control over prioritising the objects of interest as targets.

- Once a priority list is generated, the system automatically transmits the information *(Act)* on the network, with no human involvement. The system provides an update to the operator when this action is complete. This is done in "informative" mode.
- Objects that are considered as being of no interest are automatically classified and eliminated by the system. This is done in "reclusive" mode across the OODA process since this information is of no value to the operator.

A visual representation of this human swarm teaming system is provided below (Figure 1).

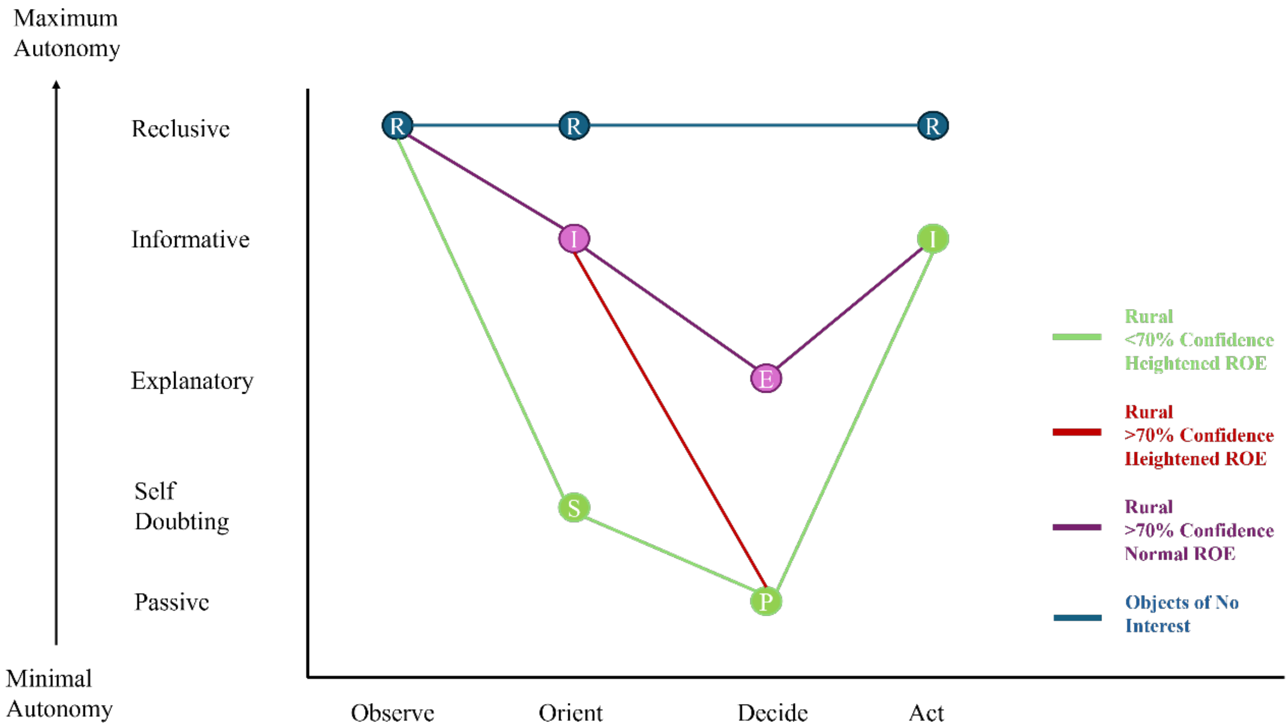
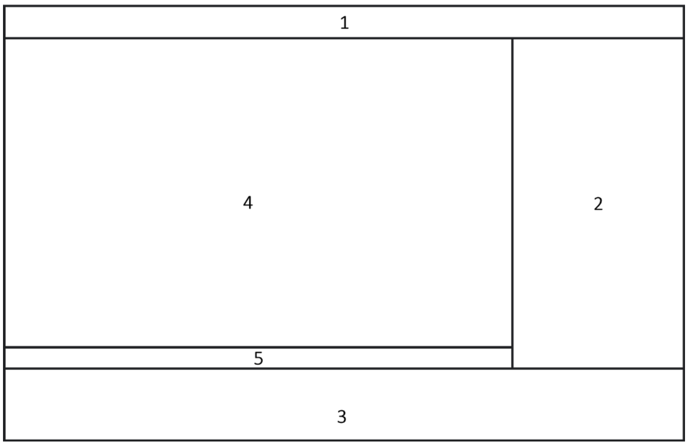


Figure 1: The proposed human swarm teaming system in action

Human-Machine Interface for Swarming

Developing a swarming HMI is a challenge very few practitioners have experienced. Knowing what the swarm is doing, sensing, and analysing is vital to effective human decision making. A swarm HMI needs to provide sufficient tactical and operational information to enable adequate operator SA, performance, trust, and teaming. An effective system needs to ensure that the human operator intervenes and acts at the right moments, especially since the frequency and quality of operator interaction with the swarm has a significant impact on mission success (Walker et al., 2012; Hocraffer & Nam, 2017; Verbruggen, 2019; Kim et al., 2020; Källbäcker & Bjurling, 2023). As mentioned, considerations like electronic warfare, jamming and limits on data transmission may prevent the system from providing real-time data. In such cases, it is prudent to instead augment information with the effective use of indicators like projected state, data-confidence and integrity metrics and information about upcoming data refreshes. These will help ensure that the human operator stays "in-the-loop" and enable effective decision making, teaming and mission success.

As part of the future swarming concept, the author designed and demonstrated a bespoke HMI for swarm command and control, underpinned by the human swarm teaming CoC described above. The initial design is based on a single screen and optimised for multi-modal inputs through touch and devices like keyboard and mouse, catering to a wider range of operator types and environments. The display is zoned according to the information being presented (see Figure 2).



1 Notifications Ribbon

2 Behaviours – Swarm Command Menu

3 Mission and Swarm State Timeline

4 Tactical Situational Display

5 Swarm Capability Metric (Health)

Figure 2: Zoning philosophy of the swarming HMI

Key to effective SA is the tactical situational display (map) which covers a large proportion of the HMI. Collapsable menus are accessible from the display edge by means of arrows (see Figure 3).

Figure 3: Mock up of drone swarm HMI

Dedicated non-directional swarm symbology positioned around the densest part of the swarm has also been developed. Read-out lines provide information on swarm call sign, location (or last known location), speed, altitude, size and availability. When communications are disrupted due to planned and unplanned circumstances, HMI modelling indicates the following (see Figure 4):

- A projected track of the swarm as per the mission plan
- Time of next data transmission from the swarm (for planned loss of communications)
- Time since contact loss (for unplanned loss of communication)
- Time of last data transmission and probable swarm location (when swarm is lost)

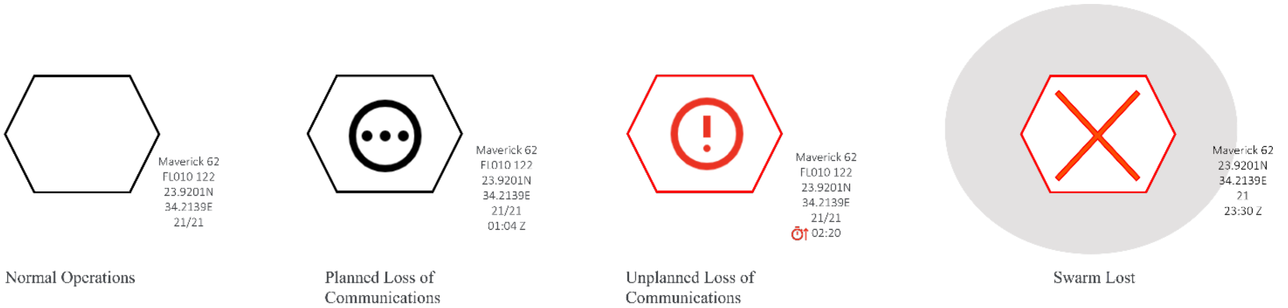


Figure 4: Swarm status depending on mission plan and transmission status

A continuously computed swarm capability metric serves as the primary "health" indicator of the swarm. It is based on mission goals, tactical data and current swarm state. When expanded, it provides further information on swarm health and mission success probability (see Figures 5 and 6).

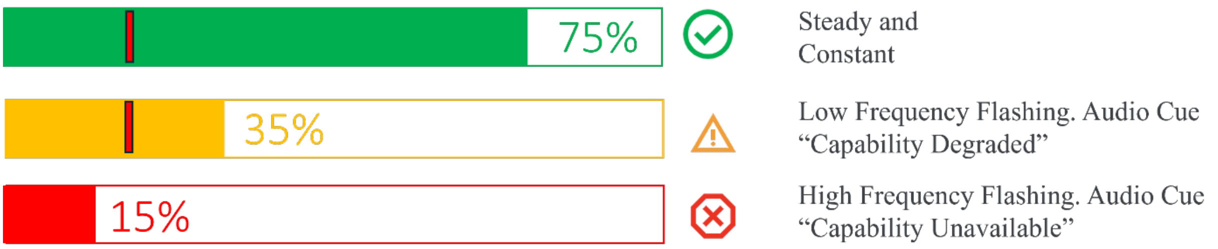


Figure 5: Continuously computed swarm capability metric. Red vertical line is the abort threshold

Figure 6: Expanded capability metric with notional information on swarm status and abort criteria

Conclusion

Drone swarming represents a step change in capability and concept of operations. While enabled by autonomy, drone swarms will not operate in isolation, with a human operator occupying an important role, conveying intent, ensuring progress and dealing with unexpected situations. The unique nature of human swarm teaming and its impact on workload, SA, fatigue and other human abilities means that current interaction systems may likely be inadequate. The proposed human swarm teaming concept integrates existing autonomy and information processing models to provide a bespoke framework founded on the dynamic sharing of tasks between the human operator and the autonomous swarm. Such an adaptive autonomy system will not only help exploit the strengths of the human operator and the drone swarm, but also ensure effective trust building, reduced workload and higher SA. This must be supported by a well-designed HMI with a focus on usable capability data, effective swarm state visualisation, means to cope with transmission losses and enabling an adequate level of information transparency for tasks, system degradation, and progress. The HMI concept presented here is currently under development and will undergo usability and human factors testing. The potential applications for swarming are constantly evolving, and the HMI concept will evolve in tandem.

References

Alberts, D., & Hayes, R. (2006). Understanding Command and Control. Technical Report. Assistant secretary of defense (C3I/Command Control Research Program)

BAE Systems. (2020). Determining a Concept of Control.

Boyd, J. R. (1996). The essence of winning and losing

Bjurling, O., Granlund, R., Alfredson, J., Mattias Arvola, & Ziemke, T. (2020). Drone Swarms in Forest Firefighting: A Local Development Case Study of Multi-Level Human-Swarm Interaction. DiVA (Linkoping University). https://doi.org/10.1145/3419249.3421239

Capiola, A., Hamdan, I. aldin, Fox, E. L., Lyons, J. B., Sycara, K., & Lewis, M. (2022). "Is something amiss?" Investigating individuals' competence in estimating swarm degradation. Theoretical Issues in Ergonomics Science, 23(5), 562–587. https://doi.org/10.1080/1463922x.2021.1983887

Chung, T., & Daniel, R. (2023). DARPA OFFSET: A Vision for Advanced Swarm Systems through Agile Technology Development and Experimentation DARPA OFFSET: A Vision for Advanced Swarm Systems through Agile Technology Development and Experimentation. Field Robotics, 3(1), 97–124. https://doi.org/10.55417/fr.2023003

Connor, J., Champion, B., & Joordens, M. (2020). Current algorithms, communication methods and designs for underwater swarm robotics: a review. IEEE Sense, 21, 153–169. https://doi.org/10.1109/JSEN.2020.3013265

Coppin, G., & Legras, F. (2012). Autonomy Spectrum and Performance Perception Issues in Swarm Supervisory Control. Proceedings of the IEEE, 100(3), 590–603. https://doi.org/10.1109/jproc.2011.2174103

Ekelhof, M. & Persi Paoli, G. (2020). Swarm Robotics: Technical and Operational Overview of the Next Generation of Autonomous Systems. UNIDIR, Geneva.

Endsley, M. R., Onal, E., & Kaber, D. B. (1997). The impact of intermediate levels of automation on situation awareness and performance in dynamic control systems. IEEE Xplore. https://doi.org/10.1109/HFPP.1997.624849

Geels-Blair, K., Rice, S., & Schwark, J. (2013). Using System-Wide Trust Theory to Reveal the Contagion Effects of Automation False Alarms and Misses on Compliance and Reliance in a Simulated Aviation Task. The International Journal of Aviation Psychology, 23(3), 245–266. https://doi.org/10.1080/10508414.2013.799355

Hocraffer, A., & Nam, C. S. (2017). A meta-analysis of human-system interfaces in unmanned aerial vehicle (UAV) swarm management. Applied Ergonomics, 58, 66–80. https://doi.org/10.1016/j.apergo.2016.05.011

Källbäcker, J., & Bjurling, O. (2023). Human-Swarm Interaction in Semi-voluntary Search and Rescue Operations: Opportunities and Challenges. Proceedings of the European Conference on Cognitive Ergonomics 2023, 1–7. https://doi.org/10.1145/3605655.3605684

Keller, D., & Rice, S. (2009). System-Wide versus Component-Specific Trust Using Multiple Aids. The Journal of General Psychology, 137(1), 114–128. https://doi.org/10.1080/00221300903266713

Kim, L., Drew, D., Domova, V., & Follmer, S. (2020). User-defined Swarm Robot Control. In Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20). Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3313831.3376814

Kolling, A., Walker, P., Chakraborty, N., Sycara, K., & Lewis, M. (2016). Human Interaction with Robot Swarms: A Survey. IEEE Transactions on Human-Machine Systems, 46(1), 9–26. https://doi.org/10.1109/thms.2015.2480801

Lyons, J. B., Capiola, A., Adams, J. A., Mator, J. D., Cherry, E., & Barrera, K. (2025). Examining the human-centred challenges of human–swarm interaction. Philosophical Transactions of the Royal Society a Mathematical Physical and Engineering Sciences, 383(2289). https://doi.org/10.1098/rsta.2024.0140

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An Integrative Model of Organizational Trust. The Academy of Management Review, 20(3), 709–734. https://doi.org/10.2307/258792

Nam, C., Walker, P., Li, H., Lewis, M., & Sycara, K. (2020). Models of Trust in Human Control of Swarms with Varied Levels of Autonomy. IEEE Transactions on Human-Machine Systems, 50(3), 194–204. https://doi.org/10.1109/thms.2019.2896845

Olsen, D., & Wood, S. (2004). Fan-out: Measuring human control of multiple robots. In Proc. SIGCHI Conf. Hum. Factors Comput. Syst., 231–238.

Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, 30(3), 286–297. https://doi.org/10.1109/3468.844354

Pendleton, B., & Goodrich, M. (2013). Scalable Human Interaction with Robotic Swarms. AIAA Infotech at Aerospace (I at A) Conference. 10.2514/6.2013-4731.

Proud, R. W., Hart, J. J., & Mrozinski, R. B. (2003). Methods for Determining the Level of Autonomy to Design into a Human Spaceflight Vehicle: A Function Specific Approach. Performance Metrics for Intelligent Systems.

Rice, S., & Geels, K. (2010). Using System-Wide Trust Theory to Make Predictions About Dependence on Four Diagnostic Aids. The Journal of General Psychology, 137(4), 362–375. https://doi.org/10.1080/00221309.2010.499397

Rice, S., Winter, S. R., Deaton, J. E., & Cremer, I. (2016). What Are the Predictors of System-Wide Trust Loss in Transportation Automation? Journal of Aviation Technology and Engineering, 6(1). https://doi.org/10.7771/2159-6670.1120

Rovira, E., McGarry, K., & Parasuraman, R. (2007). Effects of Imperfect Automation on Decision Making in a Simulated Command and Control Task. Human Factors: The Journal of the Human Factors and Ergonomics Society, 49(1), 76–87. https://doi.org/10.1518/001872007779598082

Ruff, H. A., Narayanan, S., & Draper, M. H. (2002). Human Interaction with Levels of Automation and Decision-Aid Fidelity in the Supervisory Control of Multiple Simulated Unmanned Air Vehicles. Presence: Teleoperators and Virtual Environments, 11(4), 335–351. https://doi.org/10.1162/105474602760204264

Sheridan, T., & Verplank, W. (1978). Human and computer control of undersea teleoperators. DTIC Document, Tech. Rep.

Soorati, M., Clark, J., Ghofrani, J., Tarapore, D., & Ramchurn, S. D. (2021). Designing a User-Centered Interaction Interface for Human–Swarm Teaming. Drones, 5(4), 131. https://doi.org/10.3390/drones5040131

Stanton, N., Baber, C., & Harris, D. (2008). Modelling Command and Control: Event Analysis of Systemic Teamwork. Ashgate Publishing, Ltd.

Verbruggen, M. (2019). The Question of Swarms Control: Challenges to Ensuring Human Control Over Military Swarms. Stockholm international peace research institute. Http://www.jstor.org/stable/resrep20073

Walker, P., Nunnally, S., Lewis, M., Chakraborty, N., & Sycara, K. (2013). Levels of Automation for Human Influence of Robot Swarms. Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 57(1), 429–433. https://doi.org/10.1177/1541931213571093

Walker, P., Nunnally, S., Lewis, M., Kolling, A., Chakraborty, N., & Sycara, K. (2012). Neglect benevolence in human control of swarms in the presence of latency. 2022 IEEE International Conference on Systems, Man, and Cybernetics (SMC), 3009–3014. https://doi.org/10.1109/icsmc.2012.6378253

Walliser, J. C., Ewart, & Shaw, T. H. (2023). Exploring system wide trust prevalence and mitigation strategies with multiple autonomous agents. Computers in Human Behavior, 143, 107671–107671. https://doi.org/10.1016/j.chb.2023.107671