

System Dynamics as a Framework for Human-Machine Decision Making in Command-and-control Environments

Tim Cahoe
timothy.m.cahoe@nps.edu
Naval Postgraduate School
1 University Circle, Monterey, CA 93943

Kasey Miller
millerkc@uncw.edu
University of North Carolina Wilmington
Wilmington NC 28403

Tim Shives
timothy.shives@nps.edu
Naval Postgraduate School
1 University Circle, Monterey, CA 93943

Abstract

Human-AI collaboration has emerged as a critical area of research as organizations increasingly integrate artificial intelligence into complex decision-making processes. Building on Garry Kasparov's concept of the centaur—human-machine teams that outperform either humans or AI operating independently- research has demonstrated the potential of collaborative intelligence across a range of domains. However, designing effective human-AI partnerships remains challenging in environments characterized by uncertainty, dynamic interactions, and high-consequence decisions, including defense, healthcare, emergency management, and public safety. This paper proposes a System Dynamics approach for modeling human-AI decision-making processes by representing key resources, information flows, feedback loops, and behavioral interactions within collaborative teams. Unlike static or linear models, System Dynamics captures nonlinear relationships and second- and higher-order effects that influence trust, workload, situational awareness, and decision quality over time. The resulting framework provides researchers and practitioners with a conceptual tool for analyzing, designing, and evaluating human-AI decision systems that leverage the complementary strengths of computational intelligence and human expertise, contributing to the development of more effective, transparent, and resilient AI-assisted decision support.

Keywords: Command-and-control, Decision Making, Systems Dynamics, Systems Approach

System Dynamics as a Framework for Human-Machine Decision Making in Command-and-control Environments

Tim Cahoe, Kasey Miller, Tim Shives

1. INTRODUCTION

In Isaac Asimov's classic, *The Naked Sun*, Detective Baley and his robot partner Daneel are looking into a murder case that seems to point to only one person, Dr. Thool. Daneel is convinced that the guilty party comes down to who could have possibly committed the crime based on pure circumstances. Detective Baley, however, using the knowledge built up on years of experience, doesn't feel right about Dr. Thool being the killer; he does not seem to have the motive, and his emotional state when questioned does not seem to have been in the sort of mindset to have been able to hide the murder weapon so quickly. Detective Baley cannot shake his feeling, and to the robot's annoyance, believes there must be some other explanation based on some piece of missing evidence. He quips, "Daneel, you have worked out a perfect exercise in logic, but none of it is reasonable, just the same." In the end, Detective Baley was correct in Asimov's book, but the bigger point here is that human and machine 'thinking' differ, and this can come in handy in a team or partnership.

An Information System (IS) is comprised of people, processes, and technology (Frost et al., 2011). In contemporary information systems and defense research, understanding the operational dynamics of human-machine teaming has become an urgent imperative. Recent global conflicts, such as the war in Ukraine and Houthi maritime interdictions in the Middle East, underscore the asymmetric advantage and high lethality of unmanned and autonomous systems in modern warfare (Defense Intelligence Agency, 2024). This paradigm shift mirrors insights from domain-specific decision environments; for instance, Grandmaster Garry Kasparov's development of 'centaurs'—integrated human-machine chess teams—demonstrated that a collaborative pairing consistently outperforms either a solitary human expert or an unassisted artificial intelligence engine (Kasparov, 2017). Translated into the domain of command-and-control (C2), the centaur concept implies that the optimal utilization of AI lies in the cognitive augmentation of experienced decision-makers rather than outright automation. This approach is particularly vital in C2 environments, where human commanders navigate complex, non-linear variables that machine processing can uniquely complement. However, due to severe safety, ethical, and legal liabilities inherent to high-stakes military deployments, AI integration within C2 structures has progressed far more slowly than anticipated (Tucker, 2021). A foundational barrier to this integration is the systemic lack of rigorous, overarching frameworks to model and characterize the holistic impacts of automated choices on human systemic behavior (Lai et al., 2021).

To address these operational complexities, this paper investigates the following research question: How can System Dynamics be systematically used to model, evaluate, and optimize the allocation of dynamic decisions between human operators and machine agents in complex command-and-control (C2) environments? To answer this question, we employ a System Dynamics methodology formal systems approach specifically engineered to capture structural complexity through interconnected stocks of cognitive resources, information flows, and non-linear feedback loops. By applying this framework to a military C2 human-machine team use case, we demonstrate how critical operational variables, such as semantic uncertainty and epistemic risk, are modified by the systemic dependencies inherent to the team architecture. Ultimately, this methodology moves beyond traditional linear models, providing information systems researchers with a scientifically rigorous tool to diagnose hidden structural vulnerability, while equipping systems engineers with a predictive, simulation-driven framework to design safer, more resilient human-AI teaming configurations.

The primary contribution of this research is to extend existing human-AI decision-allocation approaches by modeling how human and machine roles interact dynamically over time through feedback loops, cognitive constraints, uncertainty, and changing operational conditions. Rather than treating decision allocation as a static assignment of tasks, the System Dynamics framework enables alternative human-machine configurations to be evaluated under varying C2 conditions. In this study, optimization refers to the simulation-based comparison of these alternative configurations to identify decision allocations that improve system-level performance and resilience, rather than to a formal mathematical

optimization procedure.

2. LITERATURE REVIEW

Information Theory

Shannon (1964) laid out the initial framework for a mathematical approach to communication theory, which later developed into the broader field of Information Theory. Shannon's basic idea is that information can be measured utilizing entropy, or the freedom of possible options in communications. Weaver and Shannon (1949) note that information can be measured by the precision of communication (the accuracy problem) and that the meaning received adds to the recipient's knowledge in a way that produces the sender's intended behavior. Wickens and Hollands (2000) rightly note that Shannon's theory lacks a truth parameter—information in his theory may in fact be false. While Shannon's framework establishes how information and uncertainty can be mathematically characterized, it does not fully explain how that information is translated into action by a decision-maker. Wiener extends this foundation by connecting information and uncertainty reduction to decision-making and, ultimately, to the use of machines to support that process.

Wiener adds to the discussion of information in terms of decision-making, writing that information is what reduces the infinite number of choices before a decision-maker to viable options. When choices are nearly infinite, little information is had. When we can provide information about the options or limit them, we gain insight into the choices. Wiener also introduced the concept of computing machines, reducing human decision-making burdens through mathematical precision; in contemporary systems, this is mirrored by Large Language Models (LLMs), which mathematically collapse probability distributions to reduce state-space uncertainty (Wiener, 1948, 1950). Wiener was one of the first to posit thinking machines that could solve information problems for decision-makers by making decisions with mathematical precision.

Command-and-Control and Decision Making

Naval Doctrine Publication 6 defines command as "the authoritative act of making decisions and ordering action" and control as "the act of monitoring and influencing this action" (Naval Doctrine Publication 6, 1995). Together, command and control constitute the art and science of warfare, and the study of command and control aims to understand how a military commander can best utilize them to achieve military victory. Modern military doctrine relies on the Military Decision-Making Process (MDMP) to develop structured Courses of Action (COAs), effectively limiting tactical options to a manageable subset for the commander to evaluate. Boyd (1987) added the idea of the OODA Loop (Observe → Orient → Decide → Act) for how military commanders process decisions, with a focus on the orientation process to the environment. Later doctrine developed the idea of warfare as two competing OODA loops (Naval Doctrine Publication 6, 1995). Figure 1 illustrates the modified OODA Loop presented in NDP 6, highlighting the iterative relationship among observation, orientation, decision, and action within the command-and-control process.

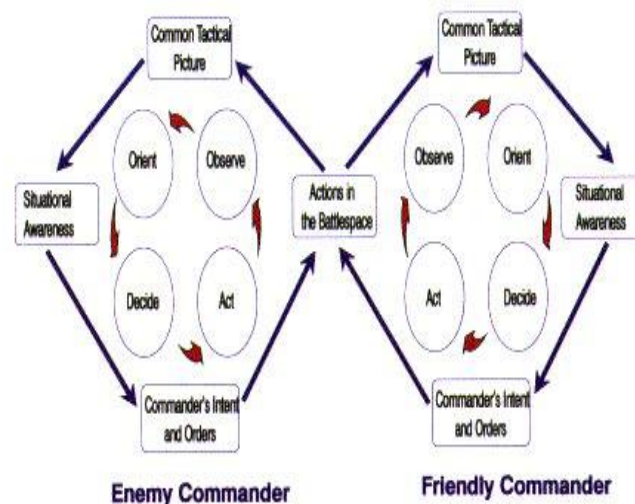


Figure 1 A modified version of Boyd's OODA Loop in the NDP 6

Van Creveld (1985) conducted a thorough review of the complexities that information technology brought to warfare, both increasing the information available to commands and increasing the ability to over-centralize command, causing information overload and decision paralysis. Builder et al. (1999) introduced the use of information technology to go beyond the commander's intent and recommended shifting to a Commander's Concept, which is more holistic in how the commander views the battlespace. Alberts and Hayes (2006) created a framework of a command-and-control (C2) organization as choices on a 3D cube with three dimensions that should be adjusted to best suit the organization: (1) allocation of decision rights, (2) patterns of interaction among the actors, and (3) distribution of information. Allocation of decision rights is the most important element and must be informed by the other two dimensions. Alberts and Hayes (2006) noted that the Napoleonic staff structure was ideal for breaking up decision-making roles during the industrial age, but that the information age requires greater decentralization of decisions due to the complexity and amount of specialization needed in modern warfare. Decision allocation is not as simple as it seems, because decision-making often evolves organically, with subordinates reporting decisions rather than asking permission. As illustrated in Figure 2, decision allocation is therefore a dynamic process shaped by the interaction of decision rights, information distribution, and patterns of interaction among participants. This perspective provides an important foundation for the System Dynamics approach used in this study, which examines how changes in these interconnected factors influence human-machine decision-making over time.

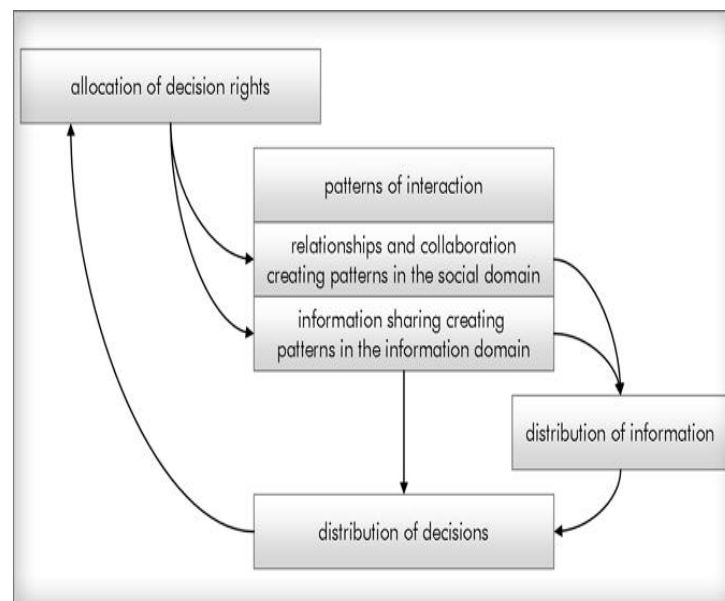


Figure 2: Dynamic Decision Allocation Diagram from Alberts and Hayes, 2006

Allocations of decisions are dynamic and represent the most crucial step of the process for a command-and-control organization or team. Deciding where a machine decision maker may have decisions allocated requires understanding what machines are particularly adept at and what humans are more proficient at in a highly dynamic environment.

Machine Decision Making

Several authors have contributed to the general definition of a thinking machine. As noted above, Wiener (1950) proposed a thinking machine that imitates the human brain by performing mathematical decision-making. Herbert Simon considered thinking machines to be Satisficers that work toward satisfactory decision choices based on probabilities (Simon, 1996). Russell (2021) views machine decision makers primarily as objective-seeking technology that accomplishes given objectives. Pearl (2018) makes a significant contribution with his causal ladder, describing ways of thinking about causes and effects. He places current thinking machines on the lowest rung of the causal inference ladder due to their limitation to statistical thinking, whereas human thinkers can imagine intervention scenarios and form counterfactual assessments.

Lai et al. (2021) highlight the lack of overarching frameworks for AI in high-stakes decision-making.

Furthermore, recent empirical research demonstrates that structured AI interventions—such as LLM summarization and multi-agent coordination—can actively reduce intrinsic cognitive load in time-constrained environments (Herm, 2023; Kosmyna et al., 2025). Kramer et al. (2018) note that people tend to be resistant to using machine decision-makers until it is explained (even without evidence) that a machine can perform the task, after which willingness increases significantly. Pomerol (1996) notes AI weaknesses in multi-attribute decision-making, which confirms Russell's (2021) point about the inability of current AI to make value judgments rather than simply seek objectives. Bolander (2019) gives a helpful framework for understanding places where machines may make erroneous decisions (in the Input Process, the Algorithm, or the Output Process). Jarrahi (2018) offers frameworks for how AI may assist human decision-making in a centaur function in specific task structures.

Decision-Making Theories

In terms of general decision theories, there are cognitive and socio-theories. In human-machine teaming, the information-processing model serves as a critical framework for understanding cognitive limits. When human operators face an influx of cues (System 2 cognitive strain), algorithmic agents can absorb the transactional load of pattern recognition, preserving human bandwidth for high-level sensemaking and value judgments (Kahneman, 2013). This model posits intuitive decisions (made quickly with little focused thought) as System 1 thinking, and slower, intentional thinking that requires a decision-making process as System 2. Klein (1993) proposed the Recognition-Primed Decision (RPD) Model of rapid decision-making, which holds that experience enables more intuitive, quick thinking in complex tasks. The information-processing model for decision-making is useful for this study (Wickens & Hollands, 2000). It involves cue receipt from the environment, which then goes through a sensemaking process using situational awareness, a diagnostic process using memory, and finally a decision. This model fits both human and machine processes and could be modeled to show the differences.

Systems Dynamics and Evaluation

Systems Dynamics originated with Wiener's (1948) concepts of systems and feedback loops, and with Forrester's (1961) explanation of diagrams using stocks and flows to analyze complex industrial organizations. Churchman (1983) later developed a systems approach that enabled scientists to break down problems and analyze them according to principles outlined by Wiener and Forrester. For Churchman, the five basic scientific considerations for the systems approach are: (1) the total system objectives and performance measures of the whole system, (2) the system's environment and fixed constraints, (3) the resources of the system, (4) the components of the system, their activities, goals, and measures of performance, and (5) the management of the system.

Once a system is broken into these components, more complex structures often missed in linear thinking can be observed. Meadows and Wright (2008) applied the Churchman/Forrester method to several real cases and developed archetypes. These archetypes address common issues through system interconnections, such as overfishing, which leads to population decline. Senge (2010) makes great use of these archetypes for organizational analysis. Most useful for our application are works by Mandl (2019) and Fredericks et al. (2008), who utilized stocks and flows to demonstrate system behavior. Work has also been done applying the systems approach to command-and-control concepts, such as via the Dynamic OODA loop (Brehmer, 2005). Figure 3 illustrates this dynamic C2 decision-making process as a continuous feedback cycle in which information collection, sensemaking, planning, and the commander's concept inform decisions and subsequent military activity. The resulting effects and frictions generate new information that feeds back into the decision process, demonstrating the interconnected and iterative nature of C2 that is well suited for analysis using System Dynamics.

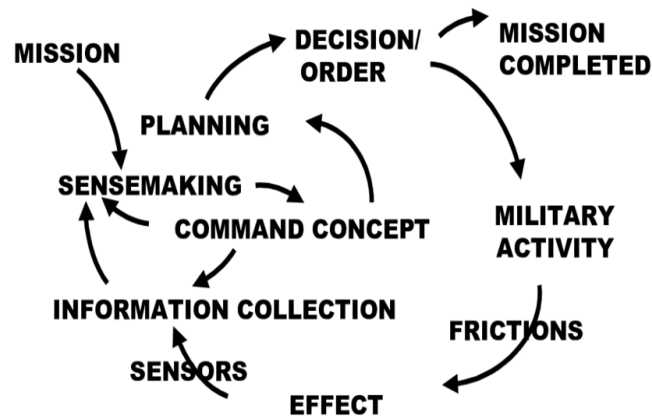


Figure 3: Dynamic OODA loop (Brehmer, 2005).

Despite these contributions, a gap remains in integrating human-machine decision allocation with a dynamic, system-level representation of C2 decision-making. Existing research provides frameworks for allocating decision rights, understanding human and machine decision capabilities, and modeling C2 processes, but these perspectives largely remain separate. Specifically, the literature lacks a System Dynamics framework that models how human cognitive constraints, machine capabilities, information flows, uncertainty, and feedback mechanisms interact over time to affect the allocation and performance of decisions within a human-machine C2 team. This study addresses this gap by integrating these elements into a simulation-based framework for evaluating alternative human-machine decision-allocation configurations.

3. METHODOLOGY

Possible Application of System Dynamics to Machine Decision Making

The operational use case for this study simulates a dynamic maritime command-and-control (C2) environment aboard a U.S. Navy surface combatant. In this architecture, the Commander is represented by the Tactical Action Officer (TAO) or Officer of the Deck (OOD), who exercises decentralized command authority on behalf of the Ship's Captain to authorize tactical maneuvering and threat engagements. The Operator serves as a watchstander, managing the ship's Common Operational Picture (COP). This system continuously ingests high-entropy data from automated sensor feeds (e.g., radar). The operator is tasked with resolving ambiguity by manually fusing disparate data streams—such as integrating unclassified Automatic Identification System (AIS) broadcast data with organic sensor tracks—to construct a coherent tactical picture. Because this continuous data fusion generates significant operator cognitive load, the scenario introduces a decision-support agent powered by a Large Language Model (LLM) utilizing a Retrieval-Augmented Generation (RAG) architecture. The machine agent acts as an algorithmic filter, querying the ship's tactical knowledge base to probabilistically assess tracks and suggest high-fidelity correlations. Crucially, while the TAO/OOD is aware of the AI's deployment, the specific mechanics of the LLM's logic and the extent of the operator's reliance on its outputs remain opaque to the commander. This epistemic friction simulates a critical systemic vulnerability: the potential for human-AI anchoring bias to unknowingly alter the COP, thereby escalating the commander's downstream decision uncertainty.

This simplified C2 architecture was intentionally selected to establish a controlled and interpretable baseline for evaluating the feasibility of System Dynamics for human-machine decision allocation. Rather than attempting to replicate the full complexity of a naval C2 environment, the model isolates the essential decision pathway among sensor inputs, the operator, machine decision support, the COP, and the commander. Limiting the initial model to these core components allows the effects of information entropy, cognitive load, and machine-assisted decision-making to be examined without introducing additional organizational and technical variables that could obscure the underlying feedback relationships. This bounded design also provides a baseline that can be systematically expanded in

future simulations to incorporate additional operators, decision agents, sensors, and command relationships.

To evaluate the feasibility of this bounded System Dynamics approach, the C2 architecture is operationalized using Churchman's (1983) five Systems Approach considerations, which provide a structured basis for defining the model's objectives, boundaries, resources, components, and management processes. Starting with the Systems Approach questions (with answers in blue):

1. The total system objectives and, more specifically, the performance measures of the whole system: **A military command-and-control system designed to get the Commander the maximum information needed at the lowest entropy possible.**
2. The system's environment fixed constraints: **System input comes in from sensors and an operator.**
3. The resources of the system: Information taken and entropy. **Higher entropy in the commander's decision-making leads to greater difficulty in rapid decision-making (the D of the OODA loop), potentially allowing the enemy force to take advantage in a conflict.**
4. The components of the system, their activities, goals, and measures of performance: **one operator, one machine decision maker prior to the operator with a database, system input, a common operational picture, and the Commander. Goals are communicated by the Commander via commander's intent.**
5. The management of the system: **The system will take information input, and decision-makers will make decisions that will keep the resulting entropy low.**

Dynamic Model

The model below demonstrates a flow of entropy across the system described above. The model most closely represents the Information Processing Decision Making Model, which takes in cues from the environment and processes that information so that decision-makers can then make a decision based on the information (Wickens & Hollands, 2000). The flow goes downstream from three points representing the reality of the operational environment.

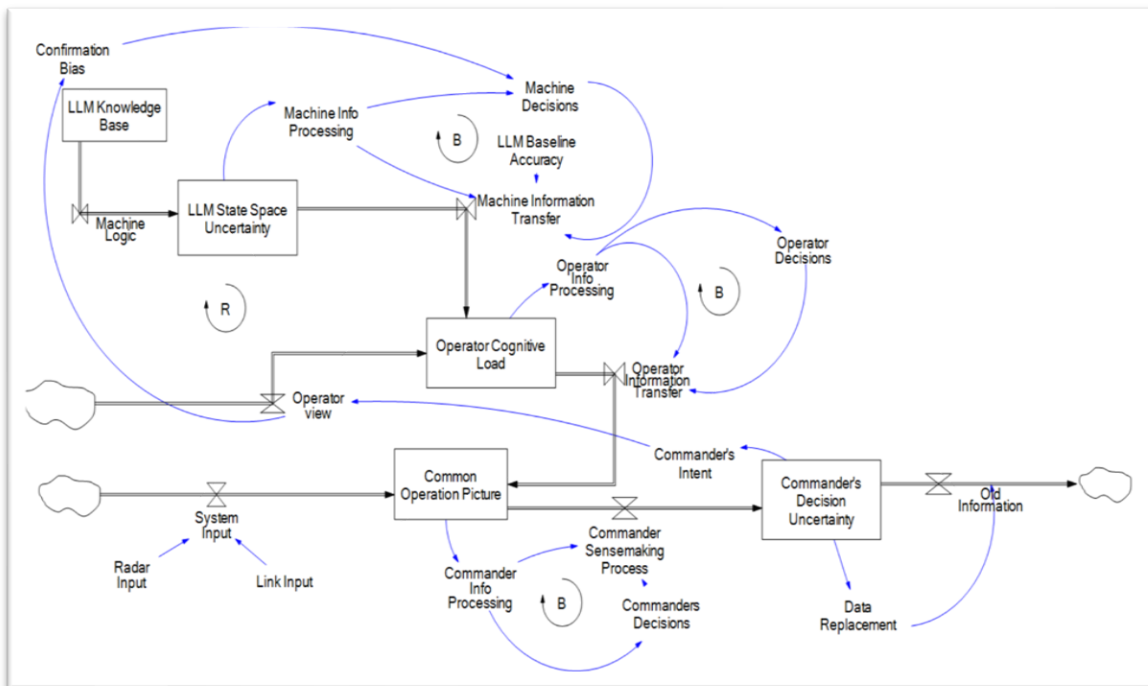


Figure 4: A Generalizable System Dynamics Diagram for Command-and-Control

In Figure 4, the rectangular elements represent System Dynamics “stocks,” or variables whose levels accumulate and change over time, including LLM state-space uncertainty, operator cognitive load, the common operational picture, and commander decision uncertainty. The connecting flows represent the rates at which information is processed, transferred, or reduced as it moves through the human-machine C2 system. This diagram conceptualizes information as a flow of uncertain variables that, if left unmitigated, can quickly overwhelm human cognitive capacity. Recent empirical research confirms that structured AI summarization and multi-agent coordination significantly reduce this intrinsic cognitive load in time-constrained environments (Herm, 2023; Kosmyna et al., 2025). When active decision-making processes are applied to raw data—such as through structural Large Language Model (LLM) summarization, operator inputs to refine a common operational picture (COP), algorithmic threat classification, or automated course of action (COA) generation—the overarching system entropy is significantly reduced. By filtering noise, enforcing rules, and absorbing the burden of pattern recognition, these AI interventions collapse the state-space of possibilities. This complementarity frees the human commander to focus on high-level moral intuition, value trade-offs, and strategic sensemaking within a cognitively manageable decision space.

This model tracks entropy as a stock, Commander’s Decision Uncertainty, that increases as information arrives via System Input from the environment (fed by Link Input and Radar Input), the Operator view of that environment, and the Machine Knowledge Base, the machine’s stored representation of reality, drawn down by Machine Logic and passed through Machine Info Processing into LLM State Space Uncertainty. Old Information, governed by Data Replacement, is transitioned out of the Commander’s Decision Uncertainty stock regularly to represent data that has been replaced. Entropy throughout, including Common Operational Picture, Operator Cognitive Load, and Commander Info Processing, is defined utilizing Shannon’s equation (Shannon, 1964).

$$H = -[p_1 \log p_1 + p_2 \log p_2 + \dots + p_n \log p_n]$$

$$H = -\sum p_i \log p_i$$

Figure 5: Shannon Entropy Equation (Shannon, 1964)

Construct Definition

Shannon entropy is used specifically as a mathematical measure of uncertainty across the available decision alternatives and is not treated as a direct measure of cognitive load, semantic uncertainty, or information quality. The entropy calculation represents a discrete probability distribution over the decision alternatives available at each stage of the C2 process, initially assuming equal probabilities ($p_i = \frac{1}{N}$). Cognitive load describes the human processing burden associated with those alternatives, while information quality reflects the reliability and relevance of information influencing their probabilities. Commander Decision Uncertainty refers to the entropy of the decision alternatives reaching the commander. These constructs are therefore related within the model but are not interchangeable.

Model Parameterization and Probability Distributions

The 90% choice reduction and 0.8 LLM accuracy used in the simulations are illustrative parameters selected to make the model’s behavioral effects observable rather than empirically calibrated operational values. Sensitivity to accuracy, choice reduction, trust/bias, and processing delay is considered when interpreting these results, and these parameters can be varied for application-specific analysis.

Entropy calculations assume a discrete uniform probability distribution in which each available decision alternative initially has equal probability. The C2 variables represent changes to this distribution:

Operator and Machine Decisions reduce N , while LLM accuracy changes the probability assigned to the machine-supported alternative and proportionally redistributes the remaining probability across other choices. Commander Decision Uncertainty represents the resulting Shannon entropy of the alternatives reaching the commander. Trust/bias and processing delay further modify how machine-generated information propagates through the decision process.

4. ANALYSIS AND DISCUSSION

There are two ways the decisions of a machine can affect entropy in a system: by reducing the number of choices, or by changing the weight or utility of the choices (Russell & Norvig, 2010). Both are represented above. Entropy is initially set as a fixed number of choices, all equal in utility. The Operator (via Operator Info Processing and Operator Decisions), the Machine (via Machine Decisions), or the Commander (via Commander's Decisions) may make choices reducing entropy at their point in the flow, passed onward as Operator Information Transfer, Machine Information Transfer, or Commander Sensemaking Process. The further downstream, the harder the effects are to observe; the closer to the Commander, the easier they are observed, particularly as Commander's Intent shapes Operator view and Confirmation Bias filters what is trusted. Machine choices take the form of the below Machine Information Transfer equation. LLM Baseline Accuracy, a number between 0 and 1, sets the probability for the final decision added via Shannon's equation, with other probabilities reduced appropriately. Machine Decisions reduces total decisions by however many the machine itself makes with incoming information. When the machine is not in the loop, this is the result we see from Commander Sensemaking Process and entropy.

Figure 6 illustrates the baseline condition in which the LLM is not included in the decision loop. Under this condition, Commander Decision Uncertainty increases over time as information and unresolved choices accumulate, while the Commander Sensemaking Process also increases as the commander processes this growing information environment. The relationship demonstrates the cognitive burden created when uncertainty must be managed primarily through human sensemaking without machine-assisted reduction of the available decision space.

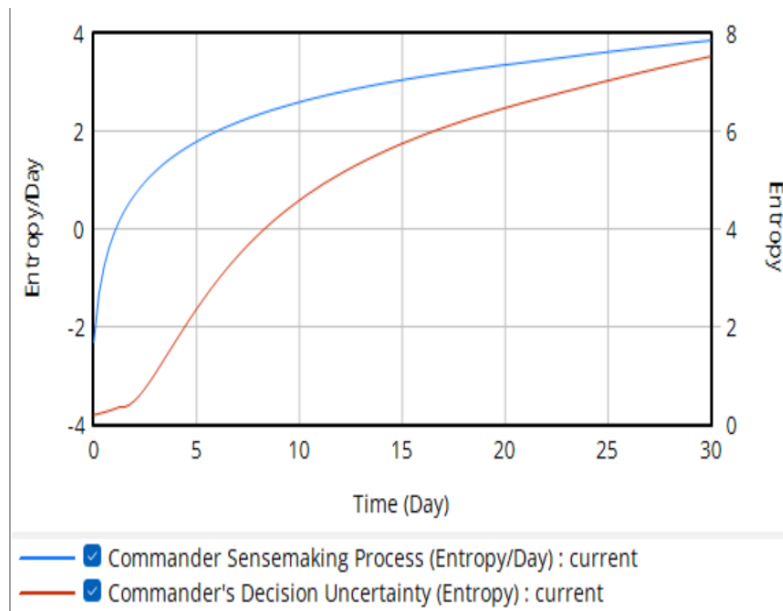


Figure 6: Baseline Commander Decision Uncertainty (No LLM)

Figure 7 demonstrates the effect of introducing Machine Decisions that reduce the available choices by 90%. Compared with the baseline condition in Figure 6, the reduction produces a modest decrease in Commander Decision Uncertainty across the simulation period. The overall trajectory remains similar, however, indicating that simply eliminating alternatives does not fundamentally change the accumulation of uncertainty. This finding suggests that the value of machine assistance depends not only on reducing the number of choices presented to the commander but also on improving the probability weighting and informational value of the remaining choices.

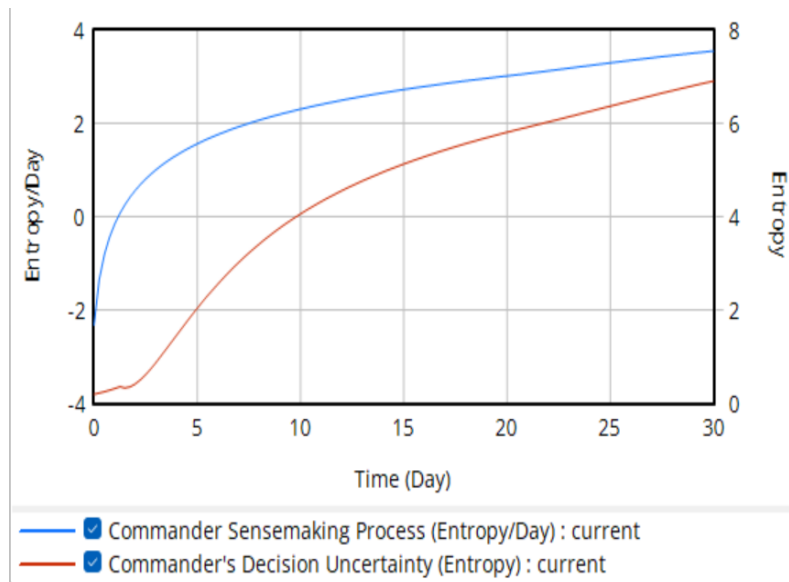


Figure 7: Commander Decision Uncertainty Given 90% Reduction in choice

The comparison between Figures 6 and 7 therefore illustrates an important distinction in the model: machine assistance can affect entropy through both choice reduction and probability weighting. The relatively modest change produced by a 90% reduction in choices suggests that filtering alone provides limited benefit when uncertainty remains associated with the alternatives that reach the commander. When a high-probability machine decision (0.8) is subsequently introduced, the model produces a stronger reduction in Commander Decision Uncertainty, demonstrating the additional effect of changing the probability distribution of the remaining choices rather than merely reducing their quantity.

When a highly accurate LLM is introduced into the decision process, the model demonstrates a more pronounced effect on Commander Decision Uncertainty. As shown in Figure 8, assigning the LLM a high-probability decision value of 0.8 changes the probability distribution of the available alternatives and reduces the entropy associated with the information reaching the commander. Compared with simply reducing the number of choices in Figure 7, this result indicates that the quality and confidence of machine-generated information can have a stronger influence on uncertainty than choice reduction alone. However, Commander Decision Uncertainty continues to increase over time, demonstrating that a highly accurate LLM by itself does not eliminate the accumulation of uncertainty within the system.

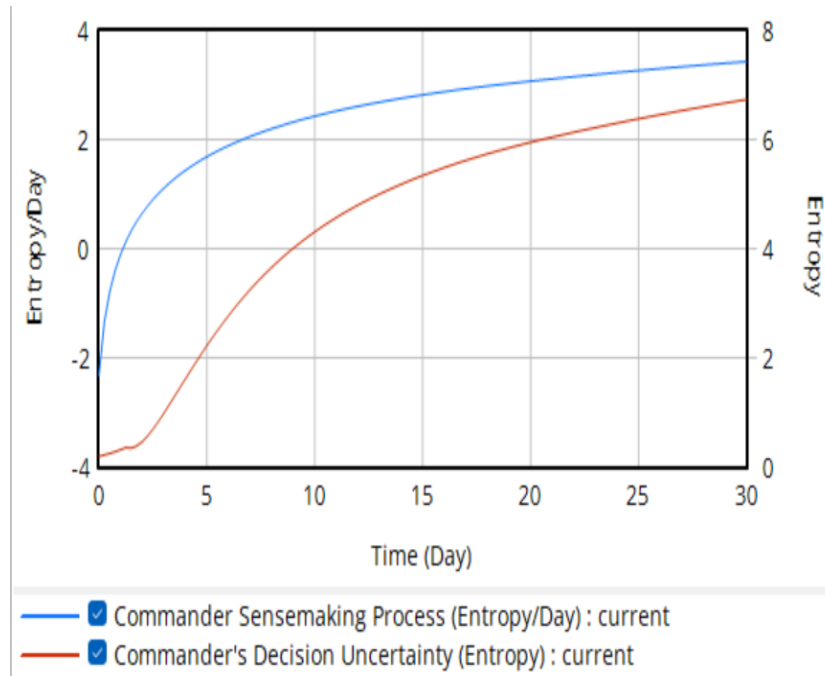


Figure 8: Commander Uncertainty Given Highly Accurate LLM

The strongest effect occurs when the two mechanisms are combined. Figure 9 shows the model when Machine Decisions both reduce the number of available choices and introduce a highly probable LLM-supported decision. Under this condition, Commander Decision Uncertainty is lower than when either mechanism is applied independently, while the Commander Sensemaking Process also requires less entropy processing over time. The comparison across Figures 7–9 therefore suggests a complementary effect: reducing the decision space decreases the quantity of information requiring consideration, while a highly accurate LLM changes the probability distribution of the remaining alternatives. Together, these mechanisms reduce the information-processing burden placed on the commander more effectively than either intervention alone.

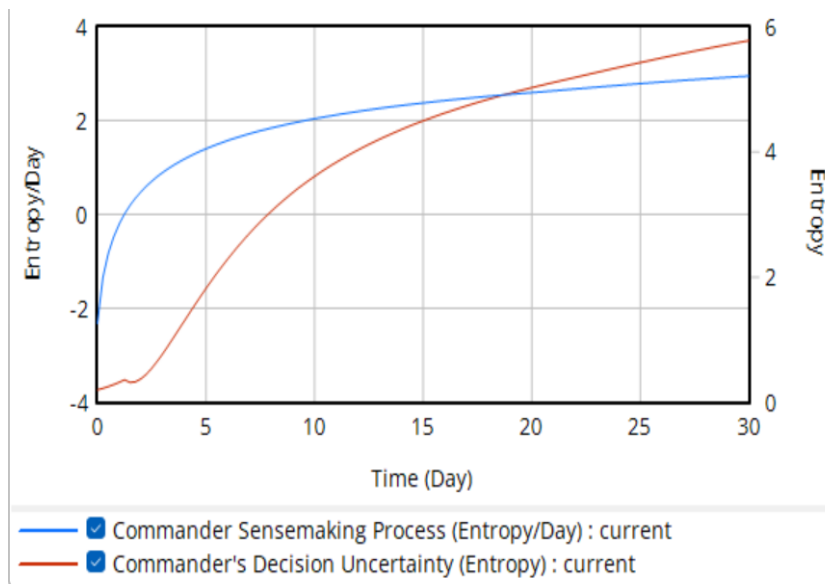


Figure 9: Commander Decision Uncertainty Given Choice Reduction and Highly Accurate LLM

The model is also sensitive to trust/bias and processing delay. One danger in the process is the effect of confirmation bias in the machine due to the operator's questions and revealed bias. This is represented as the operator's bias and affects the Machine Decisions stock in this process by multiplying a delayed bias by the percentage of decisions that the machine could potentially reduce. This delay represents the amount of possible time the machine may take to be affected by the operator's bias, and the value is set to be stronger if there is more entropy being taken in by the operator.

Initially, the entropy decreases, but as the bias affects the machine, the entropy increases with the commander. It is notable that the changes in the commander's entropy at several points that lead to jumps or lows in entropy would be hard to explain by the commander in this case because they are the result of dynamics that are due to loops that are outside of the commander's immediate input. This effect may lead to changes made in the COP or system input that would not help resolve the root issue.

This example demonstrates a generalizable model that can be built using one example stock. The diagram is useful in testing how adjustments in decision-making may affect the commander who is centrally in view in the command-and-control environment.

5. LIMITATIONS

This system dynamics model is a conceptual representation and is limited by the variables, relationships, and assumptions incorporated into the model. The simulation parameters, including LLM accuracy and choice reduction, are illustrative rather than empirically calibrated to a specific operational environment. Likewise, trust/bias and processing delays are simplified representations of complex human-machine interactions. Consequently, the results demonstrate potential system behaviors and relationships rather than predict operational outcomes. Future empirical studies should calibrate these parameters, test sensitivity across broader ranges, and validate the modeled causal relationships in operational command-and-control environments.

6. CONCLUSIONS & FUTURE WORK

There are a number of ways that this methodology may be adapted for both scientific and system design applications. For scientific application, Lai et al. (2021) have listed a number of both qualitative and quantitative measures for decision-making that could serve as potential stocks in a similar diagram. This methodology utilizing entropy itself could also be adapted to specific situations to discover potential issues or pitfalls of utilizing a machine within a command-and-control team. The effects on human-machine cooperation such as those identified by Aiken (2016) could also be modeled to demonstrate effects identified in various archetypes by Meadows and Wright (2008). In Systems Engineering, this way of diagramming a system could be utilized for applications of artificial intelligence, identifying stakeholders and assessing whether they have proper mitigations for the effects produced by the added loops introduced by bringing a decision-making machine into the system.

7. REFERENCES

- Alberts, D. S., & Hayes, R. E. (2006). *Understanding command and control*. DoD Command and Control Research Program.
- Bolander, T. (2019). *What do we lose when machines take the decisions?* Technical University of Denmark. <https://www.dtu.dk/>
- Boyd, J. R. (1987). *Organic design for command and control*. Defense and the National Interest.
- Brehmer, B. (2005). The dynamic OODA loop: Amalgamating Boyd's OODA loop and the cybernetic approach to command and control. Swedish National Defence College.
- Builder, C. H., Bankes, S. C., & Nordin, R. (1999). *Command concepts: A theory derived from the practice of command and control*. RAND.
- Churchman, C. W. (1983). *The systems approach*. Dell Publishing Co.
- Creveld, M. van. (1985). *Command in war*. Harvard University Press.

- Department of the Navy. (1995). *Naval doctrine publication 6: Naval command and control*.
- Forrester, J. W. (1961). *Industrial dynamics*. MIT Press.
- Fredericks, K. A., Deegan, M., & Carman, J. (2008). Using system dynamics as an evaluation tool. *American Journal of Evaluation*, 29(3), 251–267.
- Frost, R., Pike, J., Kenyo, L. and Pels, S. (2011), "What are information systems?," in *Business Information Systems: Design an App for That*, Saylor Foundation, pp. 9–14.
- Herm, L.-V. (2023). Impact of explainable AI on cognitive load: Insights from an empirical study. *Proceedings of the 31st European Conference on Information Systems (ECIS)*. https://aisel.aisnet.org/ecis2023_rp/269
- Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, 61(4), 577–586.
- Kahneman, D. (2013). *Thinking, fast and slow*. Farrar, Straus and Giroux.
- Klein, G. A. (1993). A recognition-primed decision (RPD) model of rapid decision making. In G. A. Klein, J. Orasanu, R. Calderwood, & C. E. Zsombok (Eds.), *Decision making in action: Models and methods* (pp. 138–147). Ablex.
- Kosmyna, N., et al. (2025). Your brain on ChatGPT: Accumulation of cognitive debt when using an AI assistant for essay writing task. *arXiv*. <https://doi.org/10.48550/arXiv.2506.08872>
- Kramer, M., Conitzer, V., Borg, J. S., & Sinnott-Armstrong, W. (2018). When do people want AI to make decisions? *Proceedings of the 2018 AAAI/ACM Conference on AI, Ethics, and Society*, 204–209.
- Lai, V., Chen, C., Liao, Q. V., Smith-Renner, A., & Tan, C. (2021). Towards a science of human-AI decision making: A survey of empirical studies. *arXiv*. <https://doi.org/10.48550/arXiv.2108.13008>
- Mandl, C. E. (2019). *Managing complexity in social systems*. Springer.
- Meadows, D. H., & Wright, D. (2008). *Thinking in systems: A primer*. Chelsea Green Publishing.
- Pomerol, J.-C. (1996). Artificial intelligence and human decision making. *European Journal of Operational Research*, 99(1), 3–25.
- Russell, S. (2021). Human-compatible artificial intelligence. In S. Muggleton & N. Chater (Eds.), *Human-like machine intelligence* (pp. 3–23). Oxford University Press.
- Senge, P. M. (2010). *The fifth discipline: The art & practice of the learning organization* (Rev. ed.). Crown.
- Shannon, C. E. (1964). The mathematical theory of communication. In C. E. Shannon & W. Weaver, *The mathematical theory of communication*. University of Illinois Press.
- Simon, H. A. (1996). *The sciences of the artificial* (3rd ed.). MIT Press.
- van Creveld, M. (1985). *Command in war*. Harvard University Press. (Note: Standardized under "van Creveld" or "Creveld" consistently as "Creveld, M. van.")
- Weaver, W., & Shannon, C. E. (1949). *The mathematical theory of communication*. University of Illinois Press.
- Wiener, N. (1948). *Cybernetics or control and communication in the animal and the machine*. MIT Press.
- Wiener, N. (1950). Cybernetics. *Daedalus*, 80(1), 2–4.
- Wickens, C. D., & Hollands, J. G. (2000). *Engineering psychology and human performance* (3rd ed.). Prentice Hall.

Appendix A

System Dynamics Terms and Definitions

Note: the table below is in logical order so that the terms build on the previous definitions.

Term	Definition	Example
System	"An interconnected set of elements that is coherently organized in a way that achieves something."	"A school, a city, a factory, a corporation, a national economy." "the earth is a system. So is the solar system; so is a galaxy..."
Vensim	"Vensim® is the software of choice for thousands of analysts, consultants, and researchers worldwide for building high-quality simulation models in business, scientific, environmental, and social systems. Vensim integrates into one environment a powerful suite of tools for developing, testing, interpreting, and distributing models. These tools include cause-and-effect diagramming, graphical and textual model construction, easy reproduction of model structure using subscripts (arrays), Monte Carlo sensitivity analysis, optimization, data handling, and application interfaces. Further features enable advanced model resolution and fidelity. Vensim includes patented techniques to aid error detection, error prevention, and rapid comprehension of complex results. Vensim is available worldwide and in a range of editions, including the fully functional Personal Learning Edition which is free for academic or personal use. To learn more, or to purchase Vensim, visit us at www.vensim.com." From https://www.ventanasystems.com/software/	The diagram for this paper is done in Vensim.
Stocks	"A stock is the foundation of the system that you can see, feel, count, or measure at any given time." "A store, a quantity, an accumulation of material or information that has built up over time." (Meadows and Wright, 2008)	"water in a bathtub, a population, the books in a bookstore, the wood in a tree, money in the bank, your own self-confidence" (Meadows and Wright, 2008)

		Also relevant to the above example: are authority, decision quality, information, trust in the information, etc. Stocks are represented as boxes in Vensim.
Flows	"Stocks change over time through the actions of a flow." (Meadows and Wright, 2008)	"Flows are filling and draining, births and deaths, growth and decay, deposits and withdrawals, successes and failures." (Meadows and Wright, 2008) Water faucet, drain, the delivery of information between people, delegation of authority from a leader to a subordinate. Flows are represented by straight double lines with arrows in the direction of the flow in Vensim.
Dynamics	The behavior over time of stocks and flows within a system.	Meadows classic example is a bathtub with the stock being the water an inflow being the faucet, and the drain being an outflow. Dynamics is how the amount of water changes over time due to adjustments on the faucet and/or drain.
Feedback Loops	"A feedback loop is a closed chain of casual connections from a stock, through a set of decisions or rules or physical laws or actions that are dependent on the level of the stock, and back again through a flow to change the stock" (Meadows and Wright, 2008)	A checking account balance which then affects how you spend funds.
Balancing Feedback Loop	"Balancing feedback loops are equilibrating or goal-seeking structures in systems and are both sources of stability and sources of resistance to change" (Meadows and Wright, 2008)	Drinking more coffee to get rid of the low energy state produced by coming down off of a coffee energy burst which keeps the tiredness level from getting to a state where the root cause is addressed with sleep.
Reinforcing Feedback Loop	An "amplifying, reinforcing, self-multiplying, snowballing" feedback loop.	Violence in war, the violent reaction to a violent action causes a greater violent reaction on the other side. (Clausewitz, 1918)

Variable	A non-stock factor that affects the system.	Interest rate and its impact on cash flow from a customer to a company,
----------	---	---

Appendix B

This model is a Vensim system dynamics representation of information-theoretic (Shannon entropy) flow through a Naval C2 human-machine team: a Commander, an Operator/watchstander, and an LLM ("Machine") that produces a shared Common Operational Picture (COP).

Below is the full breakdown.

Stocks (Levels)

Name	Formula	Naval C2 / LLM Interpretation
Commander's Decision Uncertainty	$\text{INTEG}(\text{ IF Commander Sensemaking Process} > 0 \text{ THEN } (\text{Commander Sensemaking Process} - \text{Old Information}) \text{ ELSE Old Information}, 0.2)$	The commander's accumulated entropy (ambiguity) about the tactical situation. It builds up from new sensemaking demand and is partially relieved when stale information is refreshed.
Common Operation Picture (COP)	$\text{INTEG}(\text{ (System Input + Operator Information Transfer) - Commander Sensemaking Process}, 1)$	The shared operational picture's entropy — how much unresolved information content is sitting in the COP display, fed by sensor/operator input and drained as the commander makes sense of it.
Operator Cognitive Load	$\text{INTEG}(\text{ Machine Information Transfer + Operator view - Operator Information Transfer}, 1)$	The watchstander's mental workload, driven up by machine-delivered information and their own situational "view," and relieved as they pass processed information up to the COP.
Machine Knowledge Base	$\text{INTEG}(-\text{Machine Logic}, 1000)$	The LLM's underlying reference/knowledge corpus (e.g., doctrine, sensor feeds, RAG corpus), which is slowly drawn down as logic/inference is extracted from it.
LLM State Space Uncertainty	$\text{INTEG}(\text{ Machine Logic - Machine Information Transfer}, 20)$	The LLM's internal unresolved uncertainty over its decision/state space — grows as raw logic is generated, shrinks as the model transfers resolved information to the operator.

Flows (Rates)

Name	Formula	Naval C2 / LLM Interpretation
Commander Sensemaking Process	$(\text{Commander Info Processing} - \text{Commanders Decisions}) \cdot [-(1/(\text{Commander Info Processing} - \text{Commanders Decisions})) \cdot \log_2(1/(\text{Commander Info Processing} - \text{Commanders Decisions}))] \rightarrow \text{simplifies to } \log_2(\text{Commander Info Processing} - \text{Commanders Decisions})$	Entropy the commander resolves per day converting COP content into decisions — i.e., the C2 "sensemaking" step of the OODA loop. Drains the COP stock and feeds Decision Uncertainty.
Operator Information Transfer	$(\text{Operator Info Processing} - \text{Operator Decisions}) \cdot [-(1/(\text{Operator Info Processing} - \text{Operator Decisions})) \cdot \log_2(1/(\text{Operator Info Processing} - \text{Operator Decisions}))] \rightarrow \text{simplifies to } \log_2(\text{Operator Info Processing} - \text{Operator Decisions})$. Assuming N remaining choices are equally probable, $p_i = 1/N$. Substituting this into Shannon's	Entropy the operator hands off to the COP after filtering out what they've already decided on — models the watchstander relaying machine/sensor output upward.

Name	Formula	Naval C2 / LLM Interpretation
	<i>entropy equation yields the expressions above, demonstrating that entropy simplifies to $H = \log_2 N$.</i>	
Machine Information Transfer	$-(1 - \text{LLM Baseline Accuracy}) \cdot \log_2[(1 - \text{LLM Baseline Accuracy}) / (\text{Machine Info Processing} - \text{Machine Decisions})] + \text{LLM Baseline Accuracy} \cdot \log_2(\text{LLM Baseline Accuracy})$	The rate at which the LLM converts unresolved state-space entropy into usable output for the operator, weighted by the model's baseline accuracy — the "confidence-adjusted" information the AI actually delivers.
Machine Logic	$5 \cdot [-(1/5) \cdot \log_2(1/5)] = \log_2 5$ (constant ≈ 2.32 Data/Day)	Baseline rate at which the LLM generates new inferences/logic from its knowledge base — modeled as max entropy over 5 equally likely reasoning branches.
System Input	$(\text{Link Input} + \text{Radar Input}) \cdot [-(1/(\text{Link Input} + \text{Radar Input})) \cdot \log_2(1/(\text{Link Input} + \text{Radar Input}))] \cdot 0 = 0$	Represents raw sensor/data-link entropy entering the COP. Currently zeroed out (multiplied by 0) — i.e., this pathway is switched off in this version of the model, presumably reserved for a future/expanded sensor-fusion scenario.
Old Information	Data Replacement $\cdot 0.5$	Rate at which stale commander information is "aged out" and used to offset new uncertainty — a stand-in for a CONOPS/COP refresh cycle.

Key Auxiliary / Converter Variables

Name	Formula	Naval C2 / LLM Interpretation
Commander's Intent	$= \text{Commander's Decision Uncertainty}$	The clarity (or lack thereof) of commander's intent, treated as directly tied to their current decision uncertainty — high uncertainty implies vague/shifting intent guidance down the chain.
Operator view	$\log_2 3 - 0.1 \cdot \text{Commander's Intent}$	The operator's baseline situational-awareness entropy (max entropy over 3 equally-likely readings of the scene), reduced somewhat when commander's intent is clearer.
Confirmation Bias	DELAY FIXED(IF Operator view > 10 THEN 0.5 ELSE 0.8 , 20, 1)	Models automation/confirmation bias in the human-machine team: if the operator's uncertainty spikes, trust in the machine's output drops (0.5) after a 20-day lag; otherwise a higher reliance factor (0.8) is used.
Machine Decisions	$\text{Machine Info Processing} \cdot (0.9 \cdot \text{Confirmation Bias})$	The share of machine-processed information that actually converts into accepted machine "decisions,"

Name	Formula	Naval C2 / LLM Interpretation
		discounted by how much the human trusts/confirms the AI's output.
Commander Info Processing	= Common Operation Picture	The information available to the commander for processing equals the current state of the shared COP.
Commanders Decisions	Commander Info Processing · 0.8	Fraction of COP content the commander is able to convert into actual decisions each period (an 80% decision-throughput assumption).
Operator Decisions	Operator Info Processing · 0.5	Fraction of the operator's cognitive load converted into decisions/actions (50% throughput).
Data Replacement	= Commander's Decision Uncertainty	Feeds the "refresh" mechanism — ties directly to how much uncertainty exists, driving how much old info gets replaced.
Machine Info Processing	= LLM State Space Uncertainty	The LLM's active processing load is simply its current unresolved state-space uncertainty.
Operator Info Processing	= Operator Cognitive Load	The operator's available processing capacity equals their current cognitive load stock.
LLM Baseline Accuracy	0.8 (constant)	Fixed model accuracy/confidence assumption for the LLM decision-support agent.
Link Input / Radar Input	5 / 1 (constants)	Placeholder sensor/data-link feed rates (currently disconnected from the model via the ×0 term in System Input).

Feedback Loops

Loop	Path	Type	Naval C2 / LLM Interpretation
Commander-Operator OODA Loop	CDU → Commander's Intent → Operator view → Operator Cognitive Load → Operator Info Processing → Operator Decisions → Operator Information Transfer → COP → Commander Info Processing → Commander Sensemaking Process → CDU	Balancing	The core human command-and-control cycle: commander intent shapes operator awareness, which is processed and returned as updated picture/decisions, closing the loop back on commander uncertainty. Models the OODA loop's self-correcting (or self-reinforcing, depending on parameterization) dynamics.
LLM Convergence Loop	LLM State Space Uncertainty → Machine Info Processing → Machine Information Transfer → (drains) LLM State Space Uncertainty	Balancing	As the LLM converts raw uncertainty into transferred information, its own unresolved uncertainty shrinks — models an AI agent "converging" on an answer over the engagement/session.
Confirmation Bias / Automation-Trust Loop	Operator view → Confirmation Bias (20-day delay) → Machine Decisions → Machine Information	Reinforcing/Delayed Balancing	Captures a delayed automation-bias dynamic: if operator uncertainty crosses a threshold, trust in machine output drops for a fixed period, throttling

Loop	Path	Type	Naval C2 / LLM Interpretation
	Transfer → Operator Cognitive Load → (via Commander loop) → Operator view		how much the LLM's decisions actually get absorbed — directly relevant to your Mode B/RAG-contamination trust findings.
Information Refresh (CONOPS Update) Loop	Commander's Decision Uncertainty → Data Replacement → Old Information → (subtracted from) Commander's Decision Uncertainty	Balancing	Represents periodic refresh of stale information (a natural analog to your CONOPS refresh interval parameter) — the faster/more effective this refresh, the more it caps runaway commander uncertainty.
Operator Load-Relief Loop	Operator Cognitive Load → Operator Info Processing → Operator Information Transfer → (drains) Operator Cognitive Load; and → feeds COP	Balancing	The watchstander offloads processed information into the COP, relieving their own cognitive load — a classic workload-management feedback in human-machine teaming.