

NAVAL WAR COLLEGE
Newport, R.I.

Effective Decision-Making Employing Human-Machine Teaming

A paper submitted to the Faculty of the Naval War College in partial satisfaction of the requirements of the Joint Military Operations Department and the Maritime Advanced Warfighting School (MAWS).

The contents of this paper reflect my own personal views and are not necessarily endorsed by the Naval War College or the Department of the Navy.

03-May-2022

If paper distribution is restricted in accordance with DOD Directive 5230.24, show Distribution Statement here

REPORT DOCUMENTATION PAGE			<i>Form Approved</i> <i>OMB No. 0704-0188</i>	
Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing this collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden to Department of Defense, Washington Headquarters Services, Directorate for Information Operations and Reports (0704-0188), 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302. Respondents should be aware that notwithstanding any other provision of law, no person shall be subject to any penalty for failing to comply with a collection of information if it does not display a currently valid OMB control number. PLEASE DO NOT RETURN YOUR FORM TO THE ABOVE ADDRESS.				
1. REPORT DATE (DD-MM-YYYY) 03-05-2022		2. REPORT TYPE FINAL		3. DATES COVERED (From - To) N/A
4. TITLE AND SUBTITLE Effective Decision-Making Employing Human-Machine Teaming			5a. CONTRACT NUMBER N/A	
			5b. GRANT NUMBER N/A	
			5c. PROGRAM ELEMENT NUMBER N/A	
6. AUTHOR(S) Michael Menna			5d. PROJECT NUMBER N/A	
			5e. TASK NUMBER N/A	
			5f. WORK UNIT NUMBER N/A	
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Writing & Teaching Excellence Center Naval War College 686 Cushing Road Newport, RI 02841-1207			8. PERFORMING ORGANIZATION REPORT NUMBER N/A	
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) N/A			10. SPONSOR/MONITOR'S ACRONYM(S) N/A	
			11. SPONSOR/MONITOR'S REPORT NUMBER(S) N/A	
12. DISTRIBUTION / AVAILABILITY STATEMENT Distribution Statement A: Approved for public release; Distribution is unlimited.				
13. SUPPLEMENTARY NOTES A paper submitted to the faculty of the NWC in partial satisfaction of the requirements of the curriculum. The contents of this paper reflect my own personal views and are not necessarily endorsed by the NWC or the Department of the Navy.				
14. ABSTRACT Commanders can make faster, better-informed operational-level decisions by integrating artificial intelligence with their intuition and experience. This paper examines how operational commanders rely on their subordinate commanders and robust staff to collect and analyze information to provide recommendations to aid command decision-making. If inadequate information or uncertainty is present, the commander relies on their intuition and experience to fill the gaps. Each variable in the current decision-making process has limitations in which AI technologies of big data analytics, machine learning, and neural networks aid commanders in decision-making. The paper introduces a Commander-AI Decision-Making Model (CAIDMM) synthesized within Col Boyd's Observe, Orient, Decide, & Act (OODA) loop to gain a marked advantage over an adversary. Lastly, this paper examines the "so what" and "why" operational commanders must use CAIDMM to gain a strategic advantage against near-peer competitors in today's great power competition.				
15. SUBJECT TERMS (Key words) Artificial Intelligence, Human-Machine Teaming, Machine learning, neural networks, deep learning, OODA Loop				
16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT N/A	18. NUMBER OF PAGES 31
a. REPORT UNCLASSIFIED	b. ABSTRACT UNCLASSIFIED	c. THIS PAGE UNCLASSIFIED		
			19b. TELEPHONE NUMBER (include area code) 401-841-6499	

Introduction:

The speed for decision-making effectiveness and dominance will soon exceed human cognitive capability. The United States (US) and the Joint Force must research, develop, and employ human-machine teaming to retain a competitive decision-making advantage.

According to military strategist John Boyd, Col (Ret) USAF, decision-making occurs in a recurring cycle of observe-orient-decide-act, also known as the OODA loop. The individual or organization that can process this cycle most quickly to adapt to unfolding events around them can “get inside” the opponent’s decision cycle to achieve a decisive advantage. The Department of Defense (DoD) is turning to revolutionary technologies in artificial intelligence (AI) and machine learning to process massive amounts of data and provide objective-based solutions faster than human cognitive capacity.

In today’s strategic power competition, China seeks to lead the world in AI technologies by 2030, while Russia invests in AI to weaponize technology to achieve its political and strategic objectives.^{1;2} Each country has closed the gap in military technologies by developing things such as 5th generation aircraft, hypersonic missiles, unmanned aerial systems (UAS), and anti-ship ballistic missiles that can range beyond 1,000 miles. The increased range and lethality of weapons in all domains highlights the necessity to make faster, more informed decisions at the operational level of war. Joint All-Domain Command and Control (JADC2) is DoD’s concept to connect all military sensors into a single network,

¹ Yvonne R. Masakowski, *Artificial Intelligence, and Global Security Future Trends, Threats and Considerations* (Bingley, UK: Emerald Publishing, 2020), 03.

² Note: The US leads the world in AI research and development, but Chinese students are the largest source of top-tier researchers at 29% within the US system. China uses AI facial recognition software for identity management and population control, data mining tactics to exploit world financial transactions, and image sensors to find and control the world’s natural resources. Lastly, China seeks an “Intelligentization,” which synthesizes AI technologies with everyday tasks such as logistics and transportations networks to make them safer, more reliable, faster, and more efficient than before.

or "internet of things," that would connect numerous sensors with weapons systems.³ AI-assisted JADC2 is more likely to help the decision-maker at the tactical level and not at the operational or strategic level. "DOD argues future conflicts may require leaders to make decisions within hours, minutes, or potentially seconds, compared with the current military process for analyzing the operating environment and issuing commands."⁴

Nevertheless, AI's ability to make accurate decisions in environments of uncertainty is a critical limitation where humans can use their intuition and experience to decide. Human and AI decision-making both possess strengths and weaknesses in making informed, time-sensitive decisions. How can an operational commander use Artificial Intelligence (AI) to make faster, more informed, and effective decisions to gain an advantage over an adversary?

Thesis:

For operational commanders, decision-making is an art, not a science; however, science can complement the commander to make timely, well-informed, effective decisions. Commanders can make faster, better-informed operational-level decisions by integrating artificial intelligence with their intuition and experience. One will not replace the other; but synergized together, commanders can make effective decisions to seize the initiative and generate tempo to off-balance the adversary. The Commander-AI Decision-Making Model (CAIDMM) provides a framework for commanders to make decisions using AI at the operational level.

³John R. Hoehn, "Congressional Research Service," Congressional Research Service § (2022), https://www.everycrsreport.com/files/2022-01-21_R46725_c310c14237b976901b34b7efbb95c5ddedfbb8b0.pdf, 1.

⁴John R. Hoehn, "Congressional Research Service," Congressional Research Service § (2022), https://www.everycrsreport.com/files/2022-01-21_R46725_c310c14237b976901b34b7efbb95c5ddedfbb8b0.pdf, 6.

Background:

Alan Turing claimed that as soon as a machine can act as intelligently as a human being, it can be seen as artificially intelligent.⁵ Turing achieved historical precedence by enhancing the "Bombe" cipher machine to speed up the process of breaking German encrypted messages in World War II.⁶ On May 9, 1941, the Royal Navy captured an Enigma machine, cipher key, and codebook that allowed intelligence personnel to decipher German messages. Even with the Enigma machine, the Allies still had limitations to produce actionable intelligence. Humans alone lacked the cognitive ability and time to decipher thousands of messages a day, and the "Bombe" machine alone produced inconclusive results without correct data input.⁷ Turing's invention highlights the significance of human-machine teaming to produce actionable intelligence to inform decision-making. Nevertheless, the Allied commanders maintained the responsibility to make effective decisions based on this intelligence. It was in the art of the decision to act, siphon through false information, or not act, to prevent the Germans from knowing that the Allies broke the enigma code. As a result, human-machine teaming allowed allied commanders to make faster, better-informed decisions to gain a strategic advantage.

In 2022, operational commanders still have the cognitive advantage to produce unique creative solutions. AI systems, however, are excellent at reducing vast amounts of information that interact in all aspects of warfare.⁸ Turing's introspective question of the possibility of machine intelligence has guided scientific research and development to produce

⁵ Jonathan P. Bowen, "Alan Turing: Founder of Computer Science," *Engineering Trustworthy Software Systems*, 2017, pp. 1-15, https://doi.org/10.1007/978-3-319-56841-6_1, 878.

⁶ Note: This is specifically important in the Battle of the Atlantic to protect allied shipping against German U-boat attacks

⁷ Note: Daily weather reports and "Hail Hitler" provided the baseline for the enigma code machine to be calibrated each day.

⁸ Yvonne R. Masakowski, *Artificial Intelligence, and Global Security Future Trends, Threats and Considerations* (Bingley, UK: Emerald Publishing, 2020), 22.

continually evolved intelligent operating systems that interact with humans and provide data from which humans can base their decisions.⁹

Operational Commander & Decision Making

The most important responsibility for an operational commander is to make timely and sound decisions to order their execution to achieve an objective. National Strategic and Operational Objectives guide the decision-making process while relevant information about the enemy, neutral, and friendly forces define the operational environment.¹⁰ The operational commander makes decisions based on his judgment, experience, and trust in his subordinate commanders and staff.¹¹ The commander's intuition and perception of the situation play an integral part in the decision-making process to deal with ill-structured and uncertain information environments. Many scientific studies conclude that military commanders rely more on an intuitive versus an analytical approach in highly dynamic environments.¹² Commanders rely on their intuition because of the physical limitations of their cognitive ability to analyze an overwhelming amount of information.¹³ In addition, commanders rely on their staff to collect, organize, and present that vast information to assist them in making an informed, timely decision.

The operational commander usually relies on the input from key staff members, directorate heads, and subordinate commanders to help formulate an estimate of a situation

⁹ Note: After the war, Turing published a design for the Automatic Computing Engine (ACE) which can be considered the forerunner to modern computers. In 1950, Turing published a paper, "Computing Machinery and Intelligence." The paper proposed a simple question: can machines think? As a result, Turing took a pragmatic approach with the "Imitation Game" to show that machines are intelligent if a human judge cannot distinguish between man or machine in a medium-length text-based conversation.

¹⁰ Milan E. Vego, *Joint Operational Warfare: Theory and Practice* (Newport, Rhode Island: US Naval War College, 2009), X-62.

¹¹ Milan E. Vego, *Joint Operational Warfare: Theory and Practice* (Newport, Rhode Island: US Naval War College, 2009), X-63.

¹² Malcolm Cook, Janet M. Noyes, and Yvonne Masakowski, *Decision Making in Complex Environments* (Boca Raton, FL: CRC Press, Taylor & Francis Group, 2017), 201.

¹³ Vinod U. Vincent, "Integrating Intuition and Artificial Intelligence in Organizational Decision-Making," *Business Horizons* 64, no. 4 (2021): pp. 425-438, <https://doi.org/10.1016/j.bushor.2021.02.008>, 421.

that requires a command decision. For operational planning, Commanders in the US Army use the Military Decision-Making Process (MDMP), an iterative planning methodology, to understand the situation and mission to develop a course of action.¹⁴ US Naval staffs use the Naval Planning Process (NPP) to enable fleet commanders to address complex problems and develop solutions to accomplish assigned missions. This process can become long and arduous and depends on subordinates' capacity to correctly analyze and solve operational problems. In addition, three factors limit a commander from making a timely and effective decision: information, bias, and the persistent constraint of time.

A commander is unlikely to make a timely and accurate decision if they lack relevant information. Information is crucial because it scopes the commander's knowledge and understanding of a situation. Joint Intelligence Preparation of the Operational Environment (JIPOE) is an essential analytical process used to produce intelligence assessments, estimates, and other information supporting the commander's decision-making. JIPOE is a continuous effort covering a wide range of issues relating to friendly, neutral, adversary, environmental, and civilian populace that effects operations.¹⁵ JIPOE enables the planning staff to collect unrefined data that depicts the conditions, circumstances, and influencers that affect employment capabilities. The planning team can process and exploit this data to produce quantifiable and quality information that the commander can use in making their decisions. Due to time constraints, synthesizing intelligence collection can delay a commander from deciding. If unable to collect information and create actionable intelligence, a commander might make less-informed decisions that yield unintended strategic outcomes.

¹⁴ United States, *ADRP 5-0 2019: The Operations Process* (Washington, DC, DC: Headquarters, Dept. of the Army, 2019), 1-15.

¹⁵ "JP 2-0, Joint Intelligence - Joint Chiefs of Staff," accessed March 28, 2022, https://www.jcs.mil/Portals/36/Documents/Doctrine/pubs/jp2_0.pdf, I-1.

For example, in April 1982, the British lacked operational intelligence prior to the Falklands campaign due to the low priority of collection efforts against Argentina. The British resorted to public knowledge and third-country intelligence sharing with the US and Germany to estimate Argentine military capabilities and readiness.¹⁶ As a result, the British commander proceeded with extreme caution based on unknown Argentine Air Force capabilities with anti-ship ballistic missiles. No commander will ever know all variables of a problem in planning. Therefore, a commander often relies on their knowledge, experience, and intuition to deal with uncertainty and risk. To fill the uncertainty gaps or adhere to a time constraint, a commander's bias and heuristic factor into their decision cycle.

The volatile, uncertain, complex, and ambiguous (VUCA) operating environments demand the military commander make timely, well-informed decisions. The fast tempo of operational decisions can render elaborate staff planning cumbersome, while massive intelligence collection is limited by the size and computational capacity of the analytic team.¹⁷ As a result, the commander may find themselves making intuitive decisions to deal with uncertainty. During intuitive decision-making, the commander uses mental heuristics to reduce complexity to a manageable level. These heuristics expose commanders to cognitive biases such as anchoring, availability bias, confirmation bias, and representative bias. Based on these biases, the commander may introduce errors because they are mirror imaging a decision based on past experiences; or be inept at recognizing new situations and circumstances. AI can mitigate these shortfalls and assist the commander in making fast, informed, effective decisions through objective analysis.

¹⁶ Milan E. Vego, *Joint Operational Warfare: Theory and Practice* (Newport, Rhode Island: US Naval War College, 2009), VIII-31.

¹⁷ Blair S Williams, "Heuristics and Biases in Military Decision Making," *Military Review*, October 31, 2010, pp. 40-52, 52.

Artificial Intelligence & Decision Making

One can distinguish AI into two main categories: Narrow and Artificial General Intelligence. Narrow AI is engineered for a specific purpose with limited capabilities, such as playing chess or checkers.¹⁸ Narrow AI has shown enhanced capabilities to outperform humans in specific functions but struggles in ambiguous information environments. In contrast, General AI seeks to understand and learn in different information environments, similar to the way humans process information. Simplistically, General AI attempts to *think* and display aspects of consciousness, reason, and thought.

A more refined definition of AI is, “A system's ability to interpret external data correctly, learn from such data, and use those learnings to achieve specific goals and tasks through flexible adaptation.”¹⁹ Nillson, University of Cambridge professor, provides another definition of AI. “It is the activity devoted to making machines intelligent, and intelligence is the quality that enables an entity to function appropriately and with foresight in its environment.”²⁰ Based on these two definitions, for AI to complement a commander's decision, it must collect external data of the operational environment, learn from it, produce a solution, and evaluate second- and third-order effects. Yvonne Masakowski, emerging technologies professor at the US Naval War College, asserts, “AI systems in the future will need to be reliable, intuitive, and predictive and provide validation from recommendations

¹⁸ Tannya D. Jajal, “Distinguishing between Narrow AI, General AI and Super Ai,” Medium (Mapping Out 2050, February 13, 2020), <https://medium.com/mapping-out-2050/distinguishing-between-narrow-ai-general-ai-and-super-ai-a4bc44172e22>.

¹⁹ Andreas Kaplan and Michael Haenlein, “Siri, Siri, in My Hand: Who’s the Fairest in the Land? on the Interpretations, Illustrations, and Implications of Artificial Intelligence,” *Business Horizons* 62, no. 1 (2019): pp. 15-25, <https://doi.org/10.1016/j.bushor.2018.08.004>, 15.

²⁰ Nillson, Nils s. “Artificial Intelligence.” Practical Law. Thomson Reuters, 2022. [https://uk.practicallaw.thomsonreuters.com/Glossary/UKPracticalLaw/I25ebae628e5f11e9adfea82903531a62?transitionType=Default&contextData=%28sc.Default%29&firstPage=true#:~:text=%22Artificial%20intelligence%20is%20that%20activity,of%20Ideas%20and%20Achievements%20\(Cambridge](https://uk.practicallaw.thomsonreuters.com/Glossary/UKPracticalLaw/I25ebae628e5f11e9adfea82903531a62?transitionType=Default&contextData=%28sc.Default%29&firstPage=true#:~:text=%22Artificial%20intelligence%20is%20that%20activity,of%20Ideas%20and%20Achievements%20(Cambridge)

made to the decision-maker. Sense-making and validation will be required in the future AI designs that will provide the decision-maker with actionable information.” Therefore, AI will have an expanding role in supporting the commander because AI systems will present options that reflect cognitive processing, hypothesis testing, context evaluation, and ethical considerations.²¹

IBM Watson is a prime example of the evolution of AI and the role AI affects decision-making. Watson gained notoriety in 2011 by beating human contestants in a game of Jeopardy. Since then, Watson uses a data analytics AI that processes natural language and performs analytics on vast data repositories to answer human-posed questions.²² This is important because Watson possesses cognitive and analytical capabilities to respond to human speech, process vast data stores, and provide answers to questions the company could not solve before or did not think about. Using machine learning, Watson evolves in the knowledge of the subject area and provides essential data to users and business executives.²³ Watson uses cognitive learning practices that combine data-analytics and statistical reasoning that possess unique human qualities, such as self-directed goals, common sense, and ethical values. The specific capability of AI depends on the environment and the type of problem required to be solved. AI can provide greater objectivity to assessments and limit commanders' cognitive biases. The problem-solving ability of AI is more helpful in supporting analytical rather than intuitive decision-making. AI encompasses a broad range of applications and algorithms. The specificity of Watson focuses mainly on retail, healthcare,

²¹ Yvonne R. Masakowski, *Artificial Intelligence, and Global Security Future Trends, Threats and Considerations* (Bingley, UK: Emerald Publishing, 2020), 22.

²² Mary Shacklett et al., “IBM Watson: A Cheat Sheet,” TechRepublic, July 14, 2016, <https://www.techrepublic.com/article/ibm-watson-the-smart-persons-guide/>.

²³ Mary Shacklett et al., “IBM Watson: A Cheat Sheet,” TechRepublic, July 14, 2016, <https://www.techrepublic.com/article/ibm-watson-the-smart-persons-guide/>.

and banking options. AI subsets of big data analytics and machine learning support an operational commander's decision-making ability.

Information is one key factor that influences the quality and effectiveness of the commander's decision. Big data analytic tools enable commanders to leverage massive amounts of data to make decisions.²⁴ Big data includes social media posts, clickstreams, audio and video phone calls, website log files, spatial and geolocation data, and multimedia streams. However, exponential growth in data production, storage, and computational power exceeds the human capacity to extract what is necessary and is vulnerable to irrelevant or misleading data. Big data analytics depends on the Seven Vs: volume, velocity, variety, veracity, validity, visualization, and value of the data collection.²⁵ Big data requires structured and applicable data that allows AI to recognize patterns, highlight correlations, and predict future states and outcomes.²⁶ Specifically, the commander can gain valuable insight from all the data collection from multi-domain collection efforts to determine risk within a logistic supply chain or gather battle damage assessments. Sophisticated analytics can improve decision-making, minimize risk, and uncover valuable insights from data that would otherwise remain hidden. Big data analytics can provide machine learning and AI techniques such as neural networks to produce decision trees and pattern-based analytics for the commander.

Machine learning (ML) assists command decision-making by extracting patterns and making data-based predictions from unstructured data. Machine learning is a subset of AI

²⁴ Yanfang Niu et al., "Organizational Business Intelligence and Decision Making Using Big Data Analytics," *Information Processing & Management* 58, no. 6 (August 27, 2021): pp. 2-12, <https://doi.org/10.1016/j.ipm.2021.102725>, 2-3.

²⁵ Kathleen Walch, "Big Data vs. Machine Learning: How They Differ and Relate," SearchBusinessAnalytics (TechTarget, April 27, 2021), <https://www.techtarget.com/searchbusinessanalytics/tip/Big-data-vs-machine-learning-How-they-differ-and-relate>.

²⁶ Ibid.

where machines learn from data without explicitly programmed rules or human intervention.²⁷ In ML, the computer program learns from experience with respect to a specific task and performance measures such as measures of effectiveness or measures of performance set by the operational planning team. Examples of ML functions are Google's self-driving car, Amazon and Netflix movie and advertisement recommendations, and Twitter's analysis of trending cultural events. Three subcategories of ML are supervised learning, reinforced learning, and unsupervised learning.

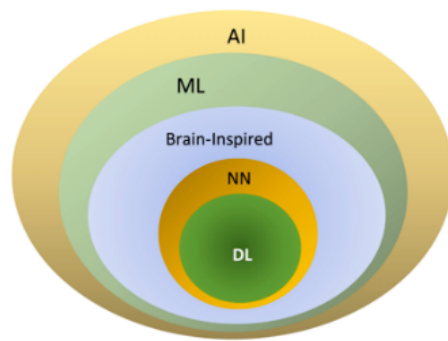


Figure 1. AI and Subfields



Figure 2. Categorization of ML/DL

Source: (Shrestha et al, 29 Sep 2020, p. 560)

Supervised learning best supports the commander's decision when historical data predicts likely future events—supervised learning algorithms use labeled examples to learn from inputs where the desired output is known.²⁸ The algorithm learns by comparing its actual input with correct outputs by using patterns, classification, data regression, and predictive values of the label²⁹. A commander can set an output such as an objective, critical

²⁷ Yash Raj Shrestha, Vaibhav Krishna, and Georg von Krogh, “Augmenting Organizational Decision-Making with Deep Learning Algorithms: Principles, Promises, and Challenges,” *Journal of Business Research*, September 29, 2020, pp. 588-603, <https://doi.org/10.2139/ssrn.3701592>, 591.

²⁸ “Machine Learning: What It Is and Why It Matters.” SAS. Accessed March 19, 2022. https://www.sas.com/en_us/insights/analytics/machine-learning.html.

²⁹ Note: Label is a term used in ML for the desired target

information requirement, or decision point, and supervised learning can continually evolve to the commander's desired outcomes.

Reinforced learning (RL) complements a commander's decision when an algorithm yields the best result by learning through trial and error. In phase zero of an operation, RL is not optimal. However, as operations progress, RL can produce actionable results. RL is used in robotics, navigation, and wargaming. RL depends on three primary components: the commander as the decision-maker, the operational environment and everything that interacts with it, and the capabilities to deal with said environment.³⁰ The commander's objective for RL is to choose the best action that achieves their objective over a given period. Good policy and doctrinal processes will significantly assist the commander in making a faster decision because the reinforced learning bases itself on best practices and policy.

Unsupervised learning aids a commander's decision because it can find unique solutions or patterns that the commander is unaware of because the system does not know the "right answer." The algorithm populates itself against data with no historical labels and aims to explore that data and find structure within.³¹ Unsupervised data can help commanders gain knowledge through transactional data to identify population trends, self-organize maps, nearest-neighbor mapping, and singular value decomposition.³² The system identifies outliers and recommends targeted courses of action based on geographic location. From this, the commander can decide and focus efforts that they did not find valuable or remove forces that

³⁰ "Machine Learning: What It Is and Why It Matters." SAS. Accessed March 19, 2022. https://www.sas.com/en_us/insights/analytics/machine-learning.html.

³¹ "Machine Learning: What It Is and Why It Matters." SAS. Accessed March 19, 2022. https://www.sas.com/en_us/insights/analytics/machine-learning.html.

³² "Machine Learning: What It Is and Why It Matters." SAS. Accessed March 19, 2022. https://www.sas.com/en_us/insights/analytics/machine-learning.html.

were not required. The last subset of ML that complements command decision-making is deep learning and neural networks.

Deep learning (DL) can change how a commander thinks about the problem they are trying to solve. DL is a subset of ML that trains a computer to perform human-like tasks, such as speech recognition, image identification, and prediction.³³ For example, everyday systems such as Amazon's Alexa and Apple's Siri are DL systems. DL is an automated and unsupervised learning process such as a neural network. Neural networks are derived from a human's brain network to have "neurons" that would "fire" when they reached a sufficient threshold from previous neuron inputs.³⁴

Neural networks can help commanders solve complex problems across the conflict continuum because the system can learn and model relationships between input and outputs that are non-linear. The neural networks can make generalizations and inferences from this learning, reveal hidden relationships and patterns, make predictions, and model highly volatile data that can offer a commander a solution or validate a pre-existing decision. Today, neural networks assist doctors in diagnosing disease, detecting credit card fraud, character and voice recognition, ecosystem evaluation, and computer vision interpretation. Neural networks can help commanders with target identification, interpret the massive amounts of imagery that depict troop movement, and, most importantly, mitigate commanders' cognitive biases.

³³ "What Is Deep Learning?," SAS, accessed March 19, 2022, https://www.sas.com/en_us/insights/analytics/deep-learning.html.

³⁴ Matthew R Voke, "Artificial Intelligence for Command and Control of Air Power," *Artificial Intelligence for Command and Control of Air Power* (2019), 16.

AI assists command decision-making within a rigid Air Tasking Order Cycle generated at the operational level.³⁵ The Air Component Commander (ACC) supports the Ground Force Commander (GFC) objectives on a 72- to 96-hour production cycle for a 24-hour execution period using the Joint Targeting Cycle (JTC) (See Figure 4). The JTC is a process of selecting and prioritizing targets and matching the correct response to them at the operational level.³⁶ AI assists commanders in target development and prioritization through near-instantaneous data analysis from multi-domain sensors that "find" a priority target. In Operation Iraqi Freedom, 2003, commanders received so much information from airborne sensors that they could not process it all.³⁷ Next, big data analytics assists to "fix" the target by collecting, organizing, and merging all sensor data to identify dynamic targets for the GFC. Machine learning algorithms can assist commanders in prioritizing sensor allocation based on the priority level of the target during the "tracking" phase and pair weapons to the shooting assist appropriate for the target. Once this is complete, the commander can review and approve air operations. In the future, DL and neural networks can run internal iterations of the joint targeting cycle by identifying targets based on big data input. Once that is complete, RL, like Netflix customers' preferences, makes recommendations of who, how, what, and where to target. Based on this information, the commander then applies their intuition, ethics, and judgment to proceed. Using AI for dynamic targeting helps the ACC support the GFC through faster target prosecution and faster decision-making to gain the initiative against our adversaries.

³⁵ Note: The joint air tasking cycle begins with the JFC's objectives, incorporates guidance received during JFC and component coordination, and culminates with an assessment of previous actions. The ATO articulates the tasking for joint air operations for a specific execution timeframe, usually 24 hours. The joint air-tasking cycle is synchronized with the JFC's battle rhythm. The JAOC typically establishes a 72- to 96-hour ATO planning cycle. Source (JP 3-30, 17 Sep 2021)

³⁶ JP 3-30, III-15

³⁷ Milan E. Vego, *Joint Operational Warfare: Theory and Practice* (Newport, Rhode Island: US Naval War College, 2009), V-III 38.

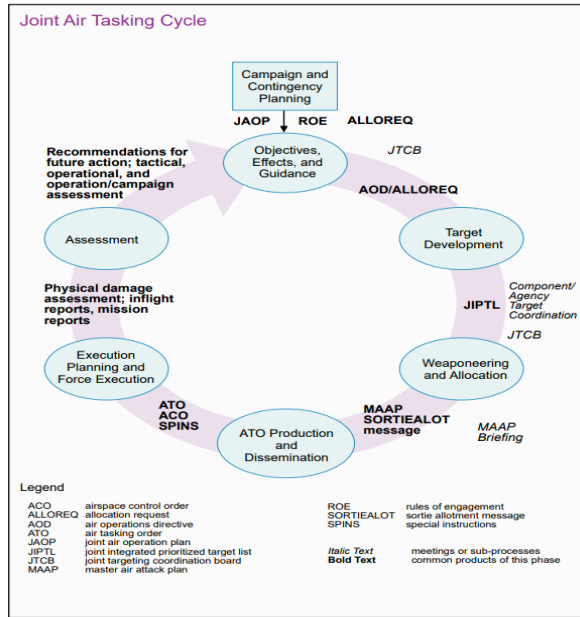


Figure III-13. Joint Air Tasking Cycle

Figure 4: Joint Air Tasking Cycle (Source JP 3-30, 17 Sep 21, p. 74)

Human-Machine Decision-Making

At the operational level of command, problems are either ill-structured or structured. Ill-structured problems mirror real-world problems where data conflicts or is inconclusive, disputants disagree about appropriate assumptions, theories, or courses of action, and ethical values are in conflict.³⁸ In contrast, structured problems are routine, commonly understood, and have a definitive answer. The commander's expertise and intuition are best suited for ill-structured problems. In contrast, logical analysis and analytics derive structured problems where human cognition cannot match the speed and processing of AI.³⁹

As previously stated, Col John Boyd's OODA loop is a strategic model and tactical framework used to describe the importance of outpacing the adversary's decision-making process. Boyd's OODA loop serves as an overarching framework for operational

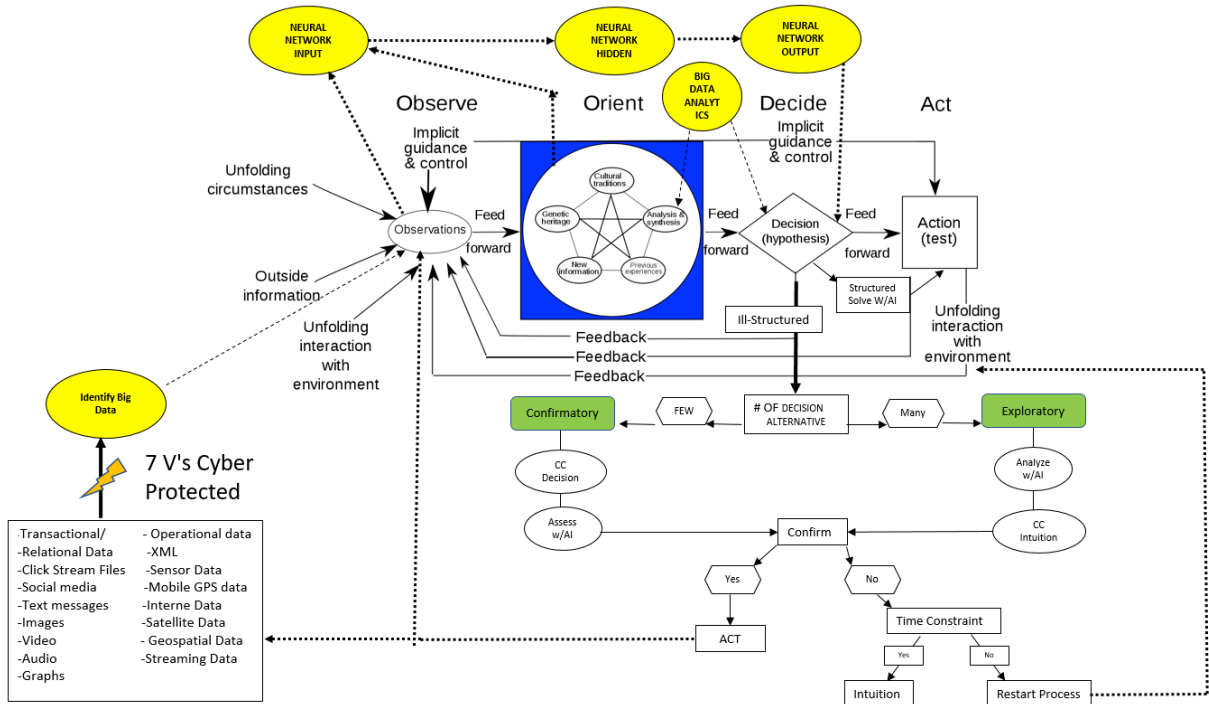
³⁸ Vinod U. Vincent, "Integrating Intuition and Artificial Intelligence in Organizational Decision-Making," *Business Horizons* 64, no. 4 (2021): pp. 425-438, <https://doi.org/10.1016/j.bushor.2021.02.008>, 427.

³⁹ Vinod U. Vincent, "Integrating Intuition and Artificial Intelligence in Organizational Decision-Making," *Business Horizons* 64, no. 4 (2021): pp. 425-438, <https://doi.org/10.1016/j.bushor.2021.02.008>, 431.

commanders' decision-making. Additionally, this section focuses on the “decision” in the OODA loop by combining Vinod Vincent’s Integrative Intuition-AI decision-making model to define how AI complements commanders' decision-making (Appendix A & Appendix B). The output is the Commander-AI Decision-Making Model (CAIDMM).

The CAIDMM begins with the observe phase, represented in Figure 3. In this phase, the commander collects all available information and data. AI complements this process through big data analytics that focuses on satellite and sensor imagery, streaming data, social media data, phone GPS data, and relational data that will feed into the outside observation. It is vital that the "big data" is structured and resilient with some form of cyber protection to ensure the security of input is legitimate information. Neural networks also take additional inputs such as command guidance, unfolding circumstances, and interaction with the environment. This phase achieves two objectives. First, massive amounts of data are being collected to analyze a structured problem. Second, unstructured data is submitted to machine-learning algorithms to synthesize, orient, and make predictions to the commander.

Figure 3: Commander-AI Decision-Making Model



The second step in the CAIDMM is the orient phase. Raw statistics, data, and information are analyzed, evaluated, and prioritized to offer insight to the commander. Specifically, with assistance from their supporting commanders and staff, the commander incorporates cultural traditions, genetic heritage, and operational experience to orient themselves to the problem. At the same time, big data analytics extracts value and knowledge from the observed data. The orient phase adds new information based on staff considerations as input for machine learning and neural networks since the synthesis of the data into a solution is unknown. Based on the interactions within the orient phase, the commander gains knowledge from two perspectives, the human and AI. These perspectives better inform a commander’s decision.

In the CAIDMM, if a problem is ill-structured, the commander decides. If the problem is structured, AI decides. AI can complement the commander in either situation

based on the number of decision alternatives. The Confirmatory and Exploratory Methods serve as two ways AI complements an ill-structured decision by the commander. The Confirmatory Method is used when the commander makes an intuitive decision and then uses AI to analyze and refine the solution. While the Exploratory Method allows AI to decide, the commander uses their intuition to refine the solution.

In the Confirmatory Method, the commander makes an intuitive decision based on the objective and desired end-state. The Confirmatory Method is most useful in situations with a limited number of decision alternatives.⁴⁰ The commander can implement the decision if AI concurs with the optimal proposed solution. ML down to DL and neural networks can use classification and regression analytics, clustering, anomaly detection, adversarial networks, and blind signal separation to assess the decision. If AI contradicts or produces inconclusive results, the commander takes two actions based on available time. If time and conditions permit, the commander reevaluates additional solutions, confirms data input into AI, and seeks an explanation until a satisfactory outcome is agreed upon. If time does not permit, the commander should make their decision based on their expertise and intuition because, in ill-structured tasks, research has proven intuitive decisions outperform analytical methods of AI.⁴¹

In contrast, the commander can use the Exploratory Method when a decision has many alternative solutions. This method allows the commander to leverage massive amounts of data by allowing AI first to identify a few sets of decision alternatives, which the

⁴⁰ Vinod U. Vincent, "Integrating Intuition and Artificial Intelligence in Organizational Decision-Making," *Business Horizons* 64, no. 4 (2021): pp. 425-438, <https://doi.org/10.1016/j.bushor.2021.02.008>, 431.

⁴¹ Vinod U. Vincent, "Integrating Intuition and Artificial Intelligence in Organizational Decision-Making," *Business Horizons* 64, no. 4 (2021): pp. 425-438, <https://doi.org/10.1016/j.bushor.2021.02.008>, 431.

commander then evaluates.⁴² Big Data Analytics, unsupervised ML, and networks can narrow the decision options and provide the commander with a few courses of action from which the commander can choose. Next, the commander implements the decision if their intuition aligns with one of the proposed actions. If not, based on time, the commander proceeds based on their expertise or restarts the decision-making process until an action can be taken.

The most important part of the CAIDMM is the requirement for continual feedback to allow human and AI algorithms to evolve. The commander's decision produces second and third-order effects that must feed into the subsequent observation phase cycle. In addition, neural networks evolve to a specific commander's thoughts and intuition, thus evolving and potentially offering more refined commander-specific solutions. Boyd's OODA loop, in its infancy, was not designed to be a mechanical cycle but a means to get inside the mind and decision cycle of the adversary.⁴³ The CAIDMM must be cyclical to leverage data to make more informed, effective, and faster decisions. The model also raises two critical factors, time and uncertainty, in the decision matrix. The goal of the CAIDMM is to reduce uncertainty as much as possible within time constraints to select the most appropriate course of action.

Limitations to Artificial Intelligence and Decision Making

In contrast to complementing the commander's decision, AI can amplify problems inherent in the decision-making process. As a result, the commander, subordinate commanders, and staff lose time due to increased workload to rectify the situation, and the

⁴² Vinod U. Vincent, "Integrating Intuition and Artificial Intelligence in Organizational Decision-Making," *Business Horizons* 64, no. 4 (2021): pp. 425-438, <https://doi.org/10.1016/j.bushor.2021.02.008>, 431.

⁴³ Robert Coram, *Boyd: The Fighter Pilot Who Changed the Art of War* (New York: Back Bay Books, 2004), 335.

commander must rely solely on their judgment.⁴⁴ In simplistic terms, the commander may make an uninformed decision. Lack of trust is the most significant limitation for commanders because of the absence of transparency within AI solutions. In addition, AI courses of action can yield considerable ethical dilemmas, and false information input can spoof command decision-making.

Even though Watson exemplifies Human-AI decision-making, its Oncology AI-based program highlights how AI hinders decision-making. The program aims at accelerating personalized patient care by analyzing critical data such as blood tests, pathology, and imaging reports that detail type, size, and the location of tumors to diagnose and offer treatment for over 12 types of cancer.⁴⁵ Although Watson learned how to scan published clinical studies, it was deemed "unsafe and incorrect" because the program could not extract and define information the same way a physician does. As a result, the doctors wrongly diagnosed patients, administered inappropriate treatments, and invested additional time and resources to alleviate the error.

At the 23rd "Multiple-Domain C2" symposium, Schubert et al. stated, "A decision support system being able to explain its recommendations is crucial for decision-makers to be able to understand and rely on the system."⁴⁶ The Future of Life Institute, a scholarly conglomerate of the leading minds in AI, highlighted the "failure of transparency" and "failure of judicial transparency" that AI cannot provide a satisfactory explanation to humans

⁴⁴ Anna Trunk, Hendrik Birkel, and Evi Hartmann, "On the Current State of Combining Human and Artificial Intelligence for Strategic Organizational Decision Making," *Business Research* 13, no. 3 (November 20, 2020): pp. 875-919, <https://doi.org/10.1007/s40685-020-00133-x>.

⁴⁵ Jo Cavallo, "Confronting the Criticisms Facing Watson for Oncology," *The ASCO Post*, September 10, 2020, <https://ascopost.com/issues/september-10-2019/confronting-the-criticisms-facing-watson-for-oncology/>.

⁴⁶ Joe Schubert et al. (23rd International Command and Control Research & Technology Symposium "Multi-Domain C2"), accessed January 31, 2022, https://www.foi.se/download/18.41db20b3168815026e010/1548412090368/Artificial-intelligence-decision_FOI-S--5904--SE.pdf, 5.2.

as to why a decision is made.⁴⁷ Therefore, the commander must decide without knowing the extent as to why. The Naval Planning Process highlights the importance of a commander's continual interaction with their team to understand the problem and offer guidance to shape the solution. In contrast, neural networks create solutions based on known input but unknown fusion. If the solution is inadequate, the commander must restart the process or decide largely based on intuition. A commander's staff can feed skewed information into the system to guide a specific outcome in extreme circumstances.

Conclusion:

The inability of advanced AI systems to be the sole decision authority emphasizes the importance of combining human expertise with AI abilities. In WWII, Turing's "Bombe" deciphered thousands of Nazi encrypted messages a day compared to just a few by brilliant mathematicians and code breakers. Most importantly, the Bombe machine supplied commanders with actionable intelligence that allowed fleet commanders to make fast, informed, and decisive decisions to save their logistics in the Atlantic Ocean by avoiding or attacking German Wolfpack U-boats. Today's great power competition depends on controlling, disseminating, and processing vast amounts of data from all domains. The speed and quantity of this data outpace the human cognitive ability to make effective informed decisions. AI allows the operational commander to manage and analyze large data sets to support decision-making. Humans and AI technologies can collaborate to deal with different aspects of decision-making. AI is well-positioned to tackle complex issues using analytical approaches. Human cognition is better suited to focus more on uncertainty and equivocality, using more creative, intuitive, and experience-based decisions. The commander and AI can

⁴⁷ Future of Life Institute, "Asilomar AI Principles," March 17, 2022, <https://futureoflife.org/2017/08/11/ai-principles/>

evolve with operations. Both entities become learning organizations, one feeding analytical data and the other providing the operational "art" to the decision, both evolving in the operational environment. The Commander-AI Decision-Making Model depicts how AI complements a commander's decision-making process and provides a matrix for operational commanders to integrate AI technologies.

Glossary:

Disclaimer these definitions are not unique or summarized by the author. These definitions are from the book *Artificial Intelligence in Medical Imaging*. The author takes no credit from this work but wants to provide the reader with generally accepted academic technical terms in the paper.⁴⁸

Artificial General Intelligence (AGI): Artificial general also known as complete, strong, super intelligence, Human Level Machine Intelligence, indicates the ability of a machine that can successfully perform any tasks in an intellectual way as the human being. Artificial superintelligence is a term referring to the time when the capability of computers will surpass humans.

Artificial Narrow Intelligence (ANI): Artificial Narrow Intelligence, also known as weak or applied intelligence, represents most of the current artificial intelligent systems which usually focus on a specific task. Narrow AIs are mostly much better than humans at the task they were made for: for example, look at face recognition, chess computers, calculus, and translation.

Artificial Neural Network (ANN): Artificial Neural Network (ANN) is a computational model in machine learning, which is inspired by the biological structures and functions of the mammalian brain. Such a model consists of multiple units called artificial neurons which build connections between each other to pass information. The advantage of such a model is that it progressively “learns” the tasks from the given data without specific programming for a single task.

Big Data: The term big data is used when traditional data mining and handling techniques cannot uncover the insights and meaning of the underlying data. Data that are unstructured or time sensitive or simply very large cannot be processed by relational database engines. This type of data requires a different processing approach which uses massive parallelism on readily available hardware

Cloud Computing: Cloud Computing enables access to and usage of shared computer resources that can be provisioned with minimum management effort. The cloud is a general metaphor to refer to a group of networked computer resources that could provide computing services to avoid up-front IT infrastructures costs.

Clustering: Clustering is a task to organize data into groups based on certain properties. Clustering analysis is widely used in data mining for pattern recognition, image analysis, and computer graphics, among others.

Cognitive computing: Cognitive computing is used to refer to the systems that simulate the human brain to help with the decision-making. It uses self-learning algorithms that perform

⁴⁸ Erik R. Ranschaert, Sergey Morozov, and Paul R. Algra, *Artificial Intelligence in Medical Imaging: Opportunities, Applications and Risks* (Cham: Springer International Publishing, 2019), Glossary.

tasks such as natural language processing, image analysis, reasoning, and human–computer interaction. Examples of cognitive systems are IBM’s Watson and Google DeepMind

Data Cleaning Data Cleaning is the process of identifying, correcting, or removing inaccurate or corrupt data records.

Data Mining Data Mining is the process of data analysis and information extraction from large amounts of datasets with machine learning, statistical approaches. and many others.

Deep Learning (DL) Deep Learning is a subfield of machine learning concerned with algorithms that are inspired by the human brain that works in a hierarchical way. Deep Learning models, which are mostly based on the (artificial) neural networks, have been applied to different fields, such as speech recognition, computer vision, and natural language processing

Heuristics A heuristic is a technique to provide fast or approximate solutions when the traditional methods are too slow or fail to give an accurate solution. A heuristic is commonly called a rule of thumb. While faster, it is typically less optimal than the classic methods it replaces

Machine Learning (ML) Machine Learning is a field in computer science that builds computational models that have the ability of “learning” from the data and then provide predictions. Depending on whether there is a supervisory signal, machine learning can be divided into three categories: the supervised learning, unsupervised learning, and reinforcement learning

Reinforcement Learning (RL) Reinforcement learning is a type of dynamic programming that trains algorithms using a system of reward and punishment. The algorithm is exposed to a total random and new dataset and it automatically finds patterns and relationships inside of that dataset. The system is rewarded when it finds a desired relationship inside of that dataset but it is also punished when finds an undesired relation. The algorithm learns from awards and punishments and updates itself continuously. This type of algorithm is always in production mode. It requires real time data to be able to update and present actions. The agent learns without intervention from a human by maximizing its reward and minimizing its penalty.

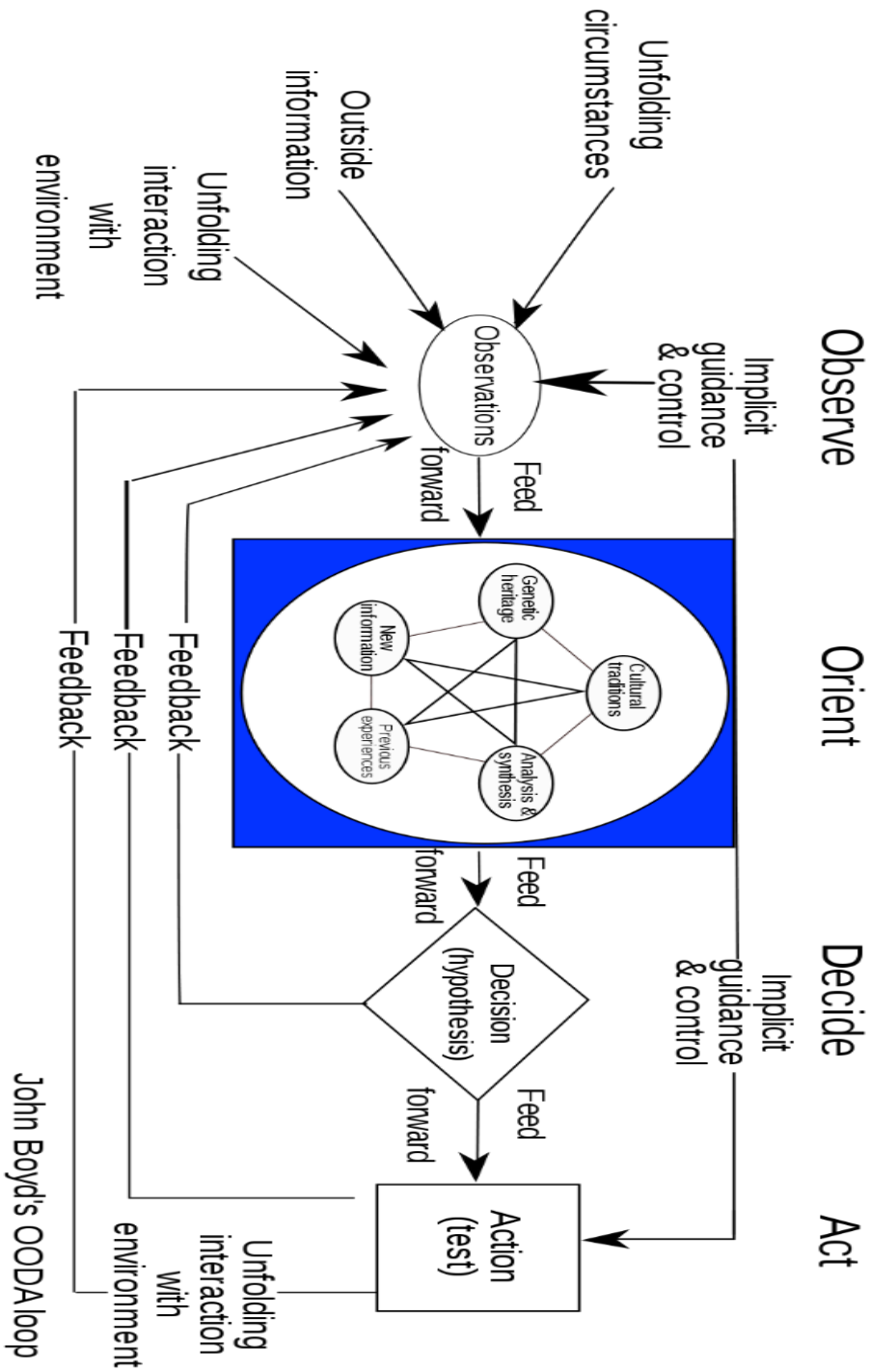
Supervised Learning (SL) Training a model from input data and its corresponding labels. Supervised machine learning is analogous to a student learning a subject by studying a set of questions and their corresponding answers. After mastering the mapping between questions and answers, the student can then provide answers to new questions on the same topic. See also unsupervised machine learning

Unsupervised learning Unsupervised learning is a type of machine learning algorithm used to draw inferences from sets of data consisting of input data without labeled responses, e.g., cluster analysis. This means that the system is exposed to a total random and new dataset and it automatically finds patterns and relationships inside of that dataset. Unsupervised learning is used in email clustering in order to distinguish between spam emails and useful emails. It

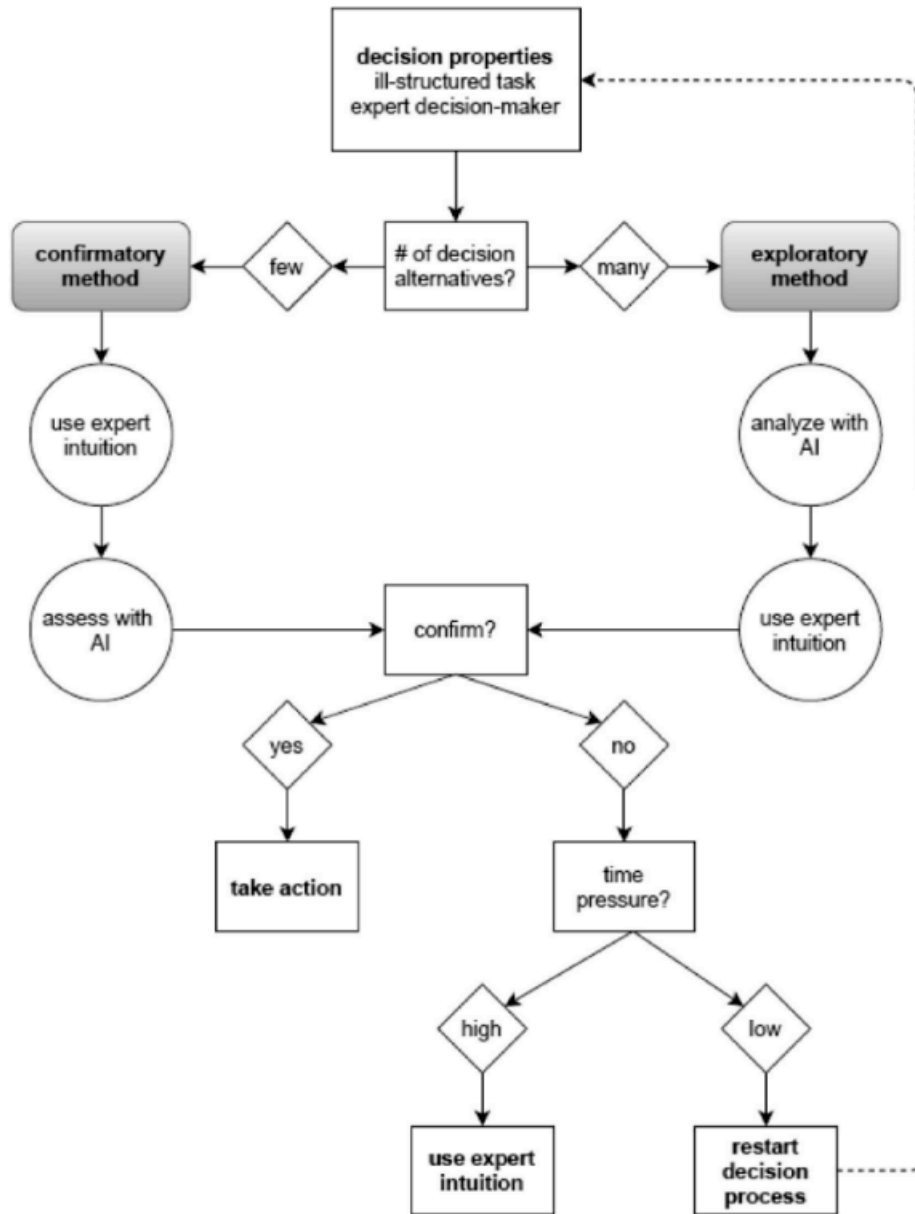
can also be seen as Learning by Example. Another example of unsupervised machine learning is principal component analysis (PCA). For example, applying PCA on a dataset containing the contents of millions of shopping carts might reveal that shopping carts containing lemons frequently also contain antacids

Turing test A test developed by Alan Turing in the 1950s that tests the ability of a machine to mimic human behavior (see terms “Computing Machinery and Intelligence”). The test involves a human evaluator who undertakes natural language conversations with another human and a machine and rates the conversations. It is designed to determine whether or not a computer could be classed as intelligent. The test (also referred to as the imitation game) is conducted by having human judges chat to several people via a computer. Most of the people the judges will be speaking to are humans, but one will actually be a chatbot. The chatbot’s objective will be to convince the human judges that they are speaking to a real person. If it does this, it has passed the Turing test.

Appendix A: Col John Boyd's OODA LOOP

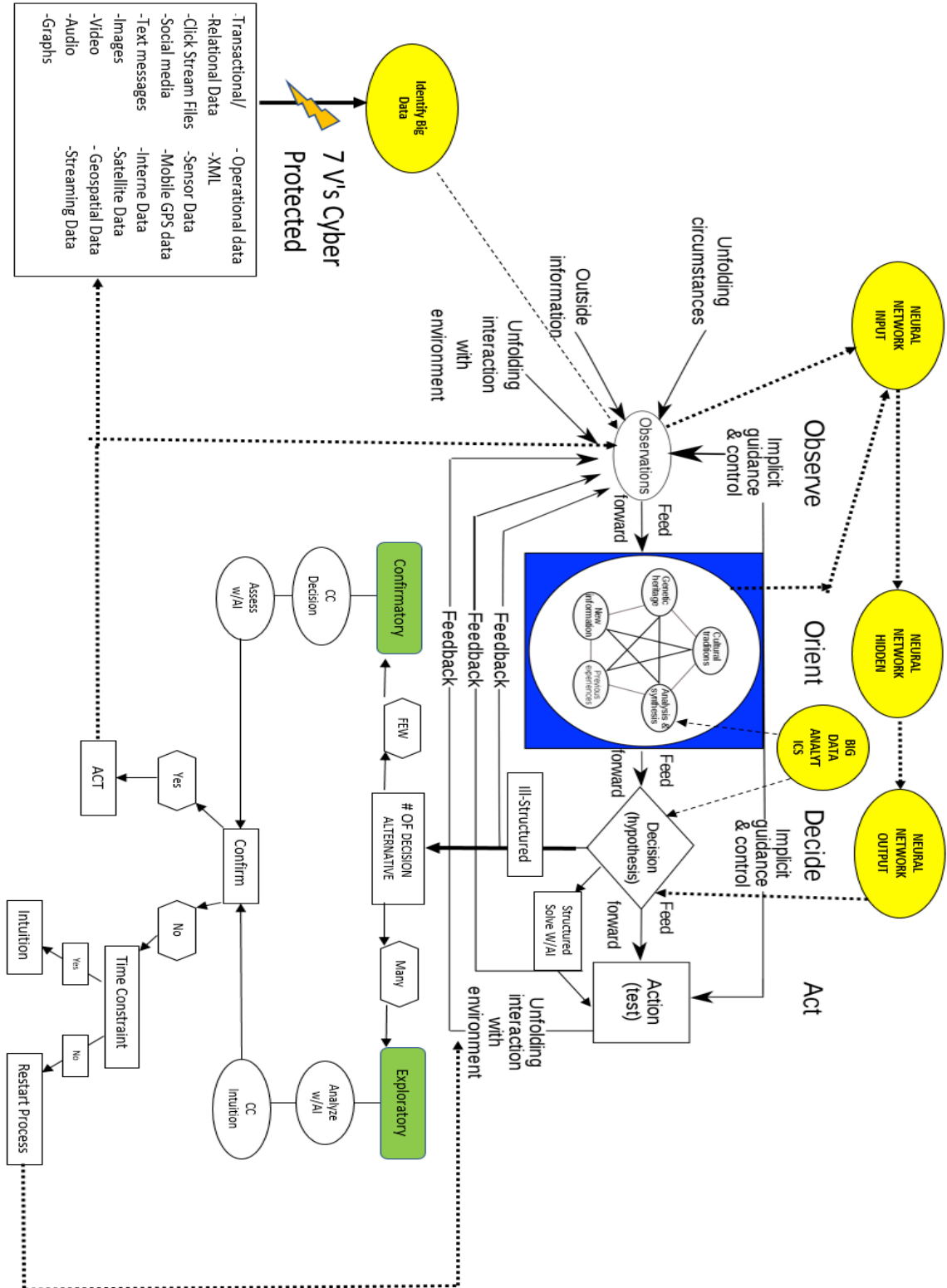


e 1. Integrative intuition-AI decision-making model



⁴⁹ Vinod U. Vincent, “Integrating Intuition and Artificial Intelligence in Organizational Decision-Making,” *Business Horizons* 64, no. 4 (2021): pp. 425-438, <https://doi.org/10.1016/j.bushor.2021.02.008>, 431.

Appendix C: Commander-AI Decision-Making Model (CAIDMM)



Bibliography

- Analyst in Military Capabilities and Programs, and John R. Hoehn, Congressional Research Service § (2022). https://www.everycrsreport.com/files/2022-01-21_R46725_c310c14237b976901b34b7efbb95c5ddedfbb8b0.pdf.
- Bowen, Jonathan P. “Alan Turing: Founder of Computer Science.” *Engineering Trustworthy Software Systems*, 2017, 1–15. https://doi.org/10.1007/978-3-319-56841-6_1.
- Branch, Major William A. “Artificial Intelligence and Operational-Level Planning: An Emergent Convergence.” Thesis, Fort Leavenworth, KS : US Army Command and General Staff College, 2018.
- Brockman, John. *Possible Minds: Twenty-Five Ways of Looking at Ai*. New York: Penguin Books, 2020.
- Cao, Guangming, Yanqing Duan, John S. Edwards, and Yogesh K. Dwivedi. “Understanding Managers’ Attitudes and Behavioral Intentions towards Using Artificial Intelligence for Organizational Decision-Making.” *Technovation* 106 (2021): 102312. <https://doi.org/10.1016/j.technovation.2021.102312>.
- Cavallo, Jo. “Confronting the Criticisms Facing Watson for Oncology.” The ASCO Post, September 10, 2020. <https://ascopost.com/issues/september-10-2019/confronting-the-criticisms-facing-watson-for-oncology/>.
- Cook, Malcolm, Janet M. Noyes, and Yvonne Masakowski. *Decision Making in Complex Environments*. Boca Raton, FL: CRC Press, Taylor & Francis Group, 2017.
- Coram, Robert. *Boyd: The Fighter Pilot Who Changed the Art of War*. New York: Back Bay Books, 2004.
- “The Global Ai Talent Tracker.” MacroPolo, June 10, 2020. <https://macropolo.org/digital-projects/the-global-ai-talent-tracker/>.
- “How Alan Turing Cracked the Enigma Code.” Imperial War Museums. Accessed March 20, 2022. <https://www.iwm.org.uk/history/how-alan-turing-cracked-the-enigma-code>.
- Hughes, Wayne P., and Robert Girrier. “Fleet Tactics and Naval Operations.” Amazon. Naval Institute Press, 2018. <https://www.amazon.com/Fleet-Tactics-Naval-Operations-Professional/dp/1682473376>.
- Jajal, Tannya D. “Distinguishing between Narrow AI, General AI and Super Ai.” Medium. Mapping Out 2050, February 13, 2020. <https://medium.com/mapping-out-2050/distinguishing-between-narrow-ai-general-ai-and-super-ai-a4bc44172e22>.
- Jarrahi, Mohammad Hossein. “Artificial Intelligence and the Future of Work: Human-AI Symbiosis in Organizational Decision Making.” *Business Horizons* 61, no. 4 (2018): 577–86. <https://doi.org/10.1016/j.bushor.2018.03.007>.
- “Joint All-Domain Command and Control: Background and ...” Congressional Research Service, March 18, 2021. <https://crsreports.congress.gov/product/pdf/R/R46725>.
- “JP 2-0, Joint Intelligence - Joint Chiefs of Staff.” Accessed March 28, 2022. https://www.jcs.mil/Portals/36/Documents/Doctrine/pubs/jp2_0.pdf.
- Kaplan, Andreas, and Michael Haenlein. “Siri, Siri, in My Hand: Who’s the Fairest in the Land? on the Interpretations, Illustrations, and Implications of Artificial Intelligence.” *Business Horizons* 62, no. 1 (2019): 15–25. <https://doi.org/10.1016/j.bushor.2018.08.004>.
- Lingel, Sherirell, Jeff Hagen, Eric Hastings, Mary Lee, Matthew Sargent, Matthew Walsh, Li Ang Zang, and David Blancett. “Joint All-Domain Command and Control for Modern

- Warfare.” RAND. Accessed January 31, 2022.
https://www.rand.org/content/dam/rand/pubs/research_reports/RR4400/RR4408z1/RAND_RR4408z1.pdf.
- Lingel, Sherrill, Jeff Hagen, Eric Hastings, Mary Lee, Matthew Sargent, Matthew Walsh, Li Ang Zhang, and David Blancett. “Joint All-Domain Command and Control for Modern Warfare: An Analytic Framework for Identifying and Developing Artificial Intelligence Applications,” 2020. <https://doi.org/10.7249/rr4408.1>.
- “Machine Learning: What It Is and Why It Matters.” SAS. Accessed March 19, 2022.
https://www.sas.com/en_us/insights/analytics/machine-learning.html.
- Masakowski, Yvonne R. *Artificial Intelligence and Global Security Future Trends, Threats and Considerations*. Bingley, UK: Emerald Publishing, 2020.
- Mukherjee, Tuneer. “Securing Maritime Commons: The Role of Artificial Intelligence in Naval Operations.” *ORF Occasional Paper*, n.d. Accessed January 31, 2022.
<https://doi.org/978-81-938214-6-6>.
- Niu, Yanfang, Limeng Ying, Jie Yang, Mengqi Bao, and C.B. Sivaparthipan. “Organizational Business Intelligence and Decision Making Using Big Data Analytics.” *Information Processing & Management* 58, no. 6 (August 27, 2021): 2–12. <https://doi.org/10.1016/j.ipm.2021.102725>.
- Ranschaert, Erik R., Sergey Morozov, and Paul R. Algra. *Artificial Intelligence in Medical Imaging: Opportunities, Applications and Risks*. Cham: Springer International Publishing, 2019.
- Schubert, Joe, Joel Brynielsson, Mattias Nilsson, and Peter Svenmarck. “Artificial Intelligence for Decision Support in Command and Control Systems.” 23rd International Command and Control Research & Technology Symposium "Multi-Domain C2". Accessed January 31, 2022.
https://www.foi.se/download/18.41db20b3168815026e010/1548412090368/Artificial-intelligence-decision_FOI-S--5904--SE.pdf.
- Shacklett, Mary, TechRepublic Staff, Brandon Vigliarolo, Lance Whitney, Moira Alexander, and William J. Francis. “IBM Watson: A Cheat Sheet.” TechRepublic, July 14, 2016.
<https://www.techrepublic.com/article/ibm-watson-the-smart-persons-guide/>.
- Shrestha, Yash Raj, Vaibhav Krishna, and Georg von Krogh. “Augmenting Organizational Decision-Making with Deep Learning Algorithms: Principles, Promises, and Challenges.” *Journal of Business Research* , September 29, 2020, 588–603.
<https://doi.org/10.2139/ssrn.3701592>.
- Spencer, David, Stephen Duncan, and Adam Taliaferro. “Operationalizing Artificial Intelligence for Multi-Domain Operations: A First Look.” *Artificial Intelligence and Machine Learning for Multi-Domain Operations Applications*, 2019.
<https://doi.org/10.1117/12.2524227>.
- States, United. *ADRP 5-0 2019: The Operations Process*. Washington, DC, DC: Headquarters, Dept. of the Army, 2019.
- Trunk, Anna, Hendrik Birkel, and Evi Hartmann. “On the Current State of Combining Human and Artificial Intelligence for Strategic Organizational Decision Making.” *Business Research* 13, no. 3 (November 20, 2020): 875–919.
<https://doi.org/10.1007/s40685-020-00133-x>.
- Vego , Milan E. *Joint Operational Warfare: Theory and Practice* . Newport, Rhode Island: US Naval War College , 2009.

- Vincent, Vinod U. “Integrating Intuition and Artificial Intelligence in Organizational Decision-Making.” *Business Horizons* 64, no. 4 (2021): 425–38.
<https://doi.org/10.1016/j.bushor.2021.02.008>.
- Voke, Major Matthew R. “Artificial Intelligence for Command and Control of Air Power.” Air University . USAF. Accessed January 31, 2022.
https://media.defense.gov/2019/Nov/27/2002218265/-1/-1/0/WF_72_VOKE_%20ARTIFICIAL_INTELLIGENCE_FOR_COMMAND_AND_CONTROL_OF_AIR_POWER.PDF.
- Voke, Matthew R. Ms. *Artificial Intelligence for Command and Control of AirPower*. Maxwell, 2019.
- Walch, Kathleen. “Big Data vs. Machine Learning: How They Differ and Relate.” SearchBusinessAnalytics. TechTarget, April 27, 2021.
<https://www.techtarget.com/searchbusinessanalytics/tip/Big-data-vs-machine-learning-How-they-differ-and-relate>.
- “What Is Deep Learning?” SAS. Accessed March 19, 2022.
https://www.sas.com/en_us/insights/analytics/deep-learning.html.
- Williams, Blair S. “‘Heuristics and Biases in Military Decision Making’ .” *Military Review* Sept-Oct , no. 2010, October 31, 2010.